

Monetary Policy Analysis and Forecasting

Prepared by Bohdan Vahalík based on the IMF Monetary Policy Analysis and Forecasting course

QPM modeling - Modul 0

VIDEO M0_1_SOFTWARE INFRASTRUCTURE 1

VIDEO M0_2_SOFTWARE INFRASTRUCTURE 2

QPM modeling - Modul 1

VIDEO M1_1_ABOUT MODUL 1

The model introduced in this course is a small macroeconomic quarterly projection model, or **QPM**. We sometimes refer to it as a **New Keynesian model**. This model is based on the ideas of monopolistic competition and features nominal rigidities:

1. The model assumes that prices are sticky, meaning that the prices do not adjust immediately as underlying costs of production change.
2. Output in the short-run is demand-determined.
3. The model equations resemble the log-linearized equations of micro-founded DSGE (dynamic stochastic general equilibrium) models, or in other words, equations that are derived from optimization problems of economic agents or firms.
4. Some parts of the model are ad hoc, so they differ from the log-linearized equations in DSGE models. Such parts usually help us better approximate the data.
5. Unlike DSGE models, equation coefficients in the QPM are not derived from deep structural parameters, such as discount factor or risk aversion, but the coefficients are directly calibrated.

In this course, we will focus on a simple version of the QPM, which we also refer to as a **canonical QPM**.

More sophisticated versions of this model are used in various central banks around the world, for example in countries like Canada, New Zealand, Sri-Lanka, Serbia, Ukraine, Belarus, Rwanda, and Malawi.

Why do we call this model a canonical QPM?

The simple version of the QPM assumes:

1. an **inflation targeting central bank**, which uses the interest rate as a key policy variable,
2. a **flexible exchange rate** determination,
3. **rational expectations**, which means that when agents build their expectations about macroeconomic variables, like inflation or exchange rate, they would use the model to project these variables, and use the projections as their best guess or expectations about the inflation and exchange rates in the future.

This model **does not** include specific features that would make it more suitable for a particular economy. For example, the model could include features such as dollarization, imperfect central bank credibility or expectation formation mechanism, which differs from rational expectations. The model could be adjusted for cases of commodity exporting countries or for countries that have a monetary policy strategy that is not inflation forecast targeting.

Also, the model **does not** include all sectors of the economy explicitly. For example, it does not feature endogenous fiscal and financial sectors, export industries etc.

These additional features could potentially be incorporated in the model, but that is beyond the scope of this course. Our goal in this course is to introduce the canonical QPM and see how it is implemented in MATLAB.

What you learn in this course will then help you build a tool, which is more suitable for a specific country.

In the previous unit, we discussed what makes the QPM a canonical model. Here are some main characteristics of the canonical QPM:

1. It is a **structural model** because each key equation has an economic interpretation, but the equations are not fully micro-founded. In other words, for every key model equation that exists in the model we can explain an underlying economic mechanism that this equation approximates. For example, how the central bank sets the interest rate or how the output is determined. We will discuss this in more detail in this module.
2. It is a **general equilibrium model** because it describes how the equilibrium is established in the economy as a whole, and not only in some particular markets or sectors.
3. The model is **stochastic** because it allows for stochastic shocks in its equations. Later in the course, you will see a set of the so-called structural shocks in the key equations for domestic variables, such as aggregate demand shock, cost push shock, exchange rate shock, and monetary policy shock.
4. This model also assumes the **rational** formation of **expectations** for inflation and exchange rate or, in other words, model-consistent expectations.
5. The QPM is a tool suitable for **monetary policy analysis and forecasting**.

Now, let's talk about the monetary policy analysis a little more:

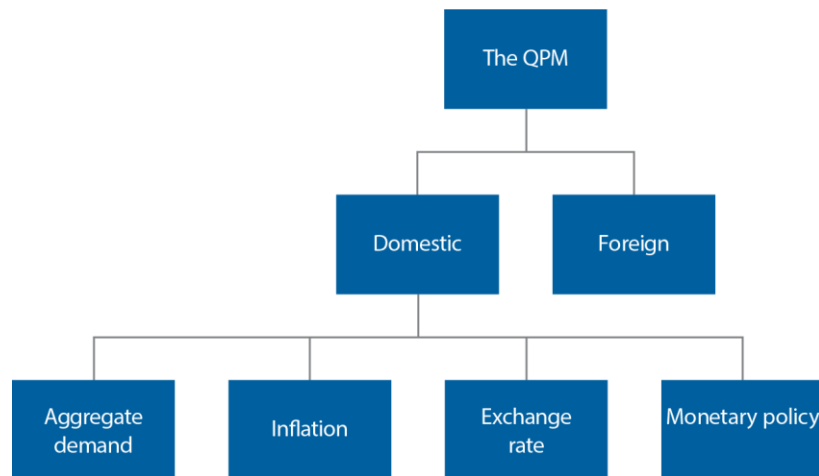
As you will see in week 2 of this module, one part of the QPM approximates the behavior of the inflation targeting central bank. In other words, the model features a monetary policy reaction function which summarizes how the central bank would change the key policy variable – the interest rate – in response to changing macroeconomic environment.

It is important to stress that this model is not a pure forecasting device as, for example, a simple reduced-form Vector-Autoregressive Model (VAR) would be.

The key purpose of our model is to help a central bank decide on an appropriate path for monetary policy, given an inflation target and the current and future macroeconomic conditions.

[VIDEO M1_2_ THE CANONICAL QPM AND THE POLICY TRILEMMA](#)

The QPM model has two large parts: domestic and foreign. The model puts emphasis on the domestic part.



The domestic part has four key blocks:

1. Aggregate demand
2. Inflation, or sometimes we call it aggregate supply block
3. Exchange rate, or uncovered interest rate parity condition
4. Monetary policy reaction function, or the interest rate policy rule

In the **domestic** part of the QPM, equations have what we call a **structural** representation.

Stylized Transmission Mechanism in the QPM: Transmission Channels

Our canonical QPM captures how changes in the key policy rate are transmitted through the economy to ultimately influence output and our key policy objective variable (inflation).

From theoretical and empirical literature, which studies monetary policy transmission, we identify **four transmission channels**¹:

1. The asset price channel, with wealth and cost of equity sub-channels
2. The credit channel, in which we further look at the bank lending and the balance sheet sub-channels
3. The interest rate channel
4. The exchange rate channel, including direct and indirect sub-channels.

In this course, we focus on the interest rate and exchange rate channels. In the developing and emerging economies, those are usually the two more important ones in monetary policy transmission mechanism. We model these channels in our canonical QPM and we will discuss them in some greater detail.

¹ Mishkin, F. 1995. "Symposium on the Monetary Policy Transmission Mechanism." Journal of Economic Perspectives. Vol. 9, #4, pp.3-10. <https://pubs.aeaweb.org/doi/pdfplus/10.1257/jep.9.4.3>; Bernanke, B. and M. Gertler, 1995. "Inside the Black Box: The Credit Channel of Monetary Policy Transmission." Working Paper #5146. NBER Working Paper Series. <https://www.nber.org/papers/w5146.pdf>; Ireland, P., 2006. "The monetary transmission mechanism." Research Department Working Papers 2006 Series #06-1. Federal Reserve Bank of Boston. <https://www.bostonfed.org/-/media/Documents/Workingpapers/PDF/wp0601.pdf>; Boivin, J., Kiley, M. and F. Mishkin, 2010. "How Has the Monetary Transmission Evolved Over Time." Working Paper #15879. NBER Working Paper Series. <https://www.nber.org/papers/w15879.pdf>

Stylized Transmission Mechanism in the QPM: Interest Rate and Exchange Rate Channels

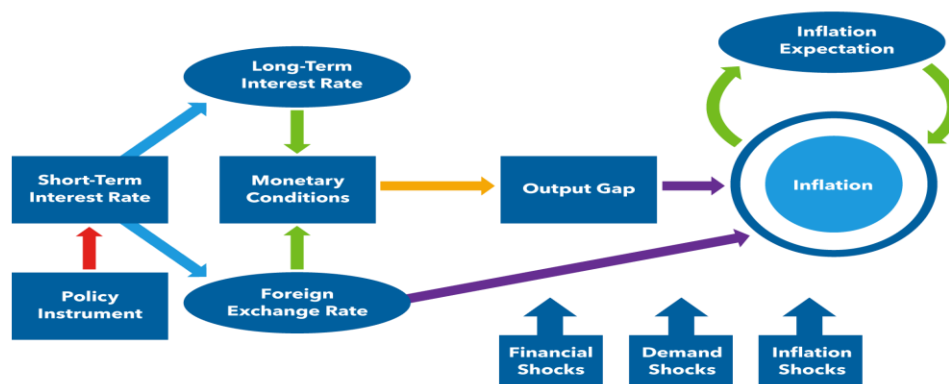
The policy transmission mechanism that we approximate in our QPM is relatively simple and focuses on two channels; **the exchange rate** and **interest rate channels**.

In the videos below, you will learn more about these channels.

[VIDEO M1_3_INTEREST RATE CHANNEL](#)

[VIDEO M1_4_EXCHANGE RATE CHANNEL](#)

In these videos we talked about the monetary policy transmission channels. The graphical representation of these channels together will give us a full description of the monetary policy transmission mechanism, which is approximated by our canonical QPM:



The transmission starts with the current and expected changes in the **policy instrument**. In our model this means that the key policy rate affects the current **short-term interest rate** and its expected levels. This in turn is transmitted to changes in the **longer-term rates**, which alters **aggregate monetary conditions**, **aggregate demand** and **output**, and ultimately **inflation**. This is the interest rate channel.

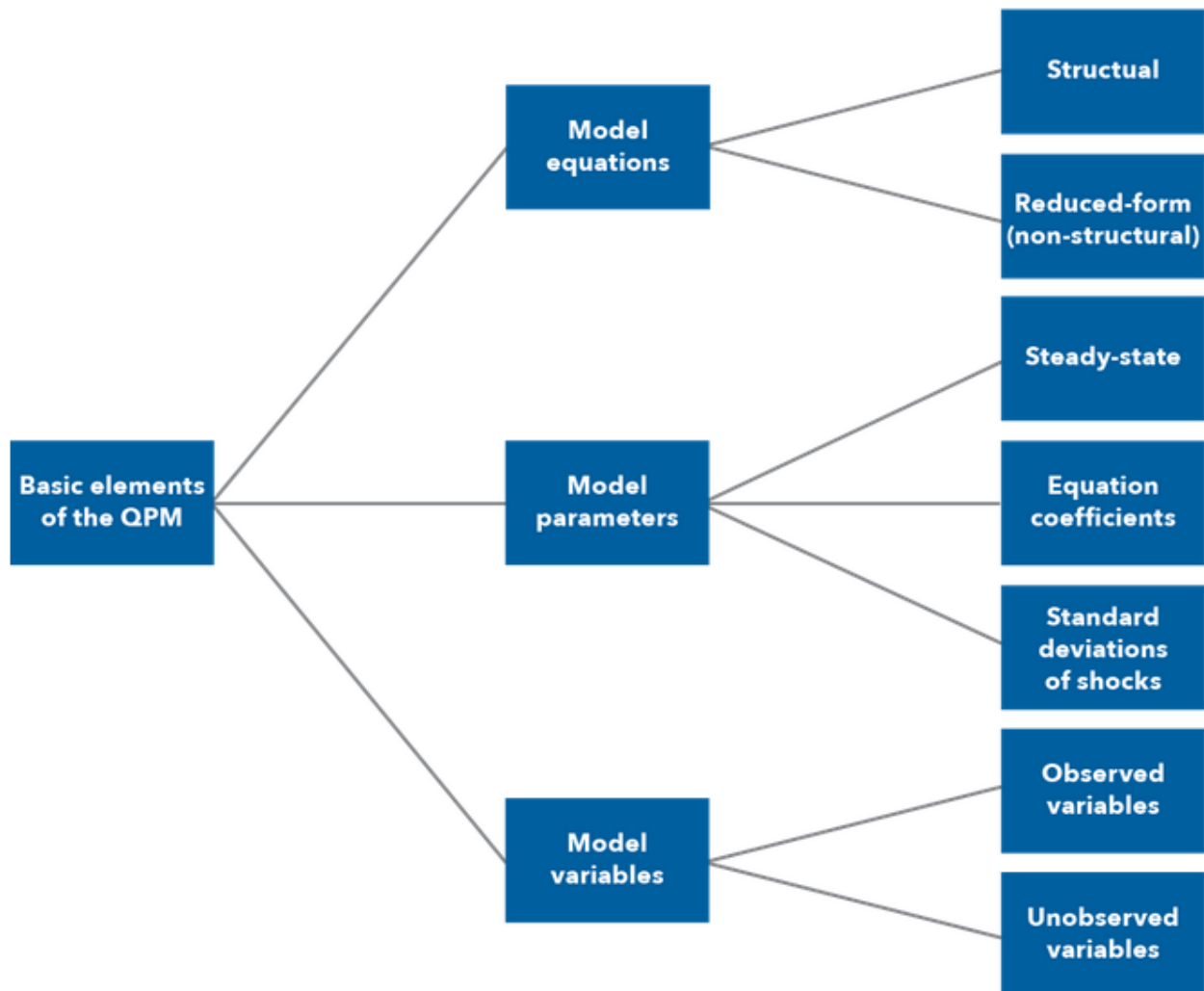
Changes in the interest rate also affect the **nominal exchange rate**, which is assumed to be flexible in the canonical setup. Further, changes in the exchange rate affect inflation directly via the cost of imported factors of production, and indirectly via changes in the relative prices of imported goods vis-à-vis domestic, and the corresponding shifts in aggregate demand between imported and domestic goods. Because of the changes in aggregate demand for domestically produced goods, domestic output and domestic cost pressures change as well, which then affects inflation.

The economy, and therefore the monetary policy transmission, is impacted by various shocks. We account for some of these shocks explicitly in our QPM. For example, the aggregate demand shock, cost push shocks, shocks to the nominal exchange rate and monetary policy shock – shock to the interest rate.

Elements of the QPM: Basic Elements

The building elements of the canonical QPM can be classified in three main dimensions: **model equations**, **model parameters** and **model variables**.

As you see here, the equations that appear in the model are classified as structural and reduced-form, or non-structural. Model parameters can be separated into three groups: parameters that describe the model's steady-state, equation coefficients and standard deviations of shocks. Model variables can be categorized as the observed and unobserved variables. In the following units, we will talk about each of these elements in greater detail.



Elements of the QPM: Equations

The main difference between equations in the structural and reduced forms is that **we can provide a macroeconomic motivation to represent the structural form**, but **macroeconomic motivation is limited for equations in the reduced-form**.

| Structural Equations | Reduced Form Equations |
|---|---|
| Macroeconomic motivation | Autoregressions with limited macroeconomic motivation |
| Examples: Monetary policy reaction function; Phillips curve | Examples: Long-term rate of output growth |

Several key stochastic equations for the domestic variables in the QPM are in the structural form.

The way the structural equations are named represents the economic essence of such equations.

In the second part of Module 1, we will introduce a **structural equation** for the domestic interest rate. The equation is called the **Monetary Policy Reaction Function or the Policy Rule**. The **Phillips curve** is the equation that describes **the relationship between the inflation and real marginal costs**. This equation also belongs to the category of structural equations.

In contrast, equations in a **reduced form** usually describe the dynamics of a variable, but do not tell us much about the economics of the underlying processes. In fact, we often use **simple autoregressions** in such cases. The **long-term (potential) rate of economic growth** will be described in our model using an autoregressive process.

Elements of the QPM: Variables

There are two types of variables in our QPM: observable and unobservable:

Observable: Information for observable variables is usually gathered and published by statistical offices or other institutions. In other words, such **variables are measured**. A variable for which we can find values in some statistical datasets compiled by Statistical Committees, Central banks, Ministries of Finance, etc. is typically an observed variable. The consumer price indices, output volume, rate of economic growth, industrial production, unemployment rate, interest rates, and exchange rates are among the observed variables.

Unobservable: In contrast, unobserved variables may not be immediately available from the statistical databases and would need to be inferred or, in other words, **estimated from the observed information using some statistical techniques**. This also means that the estimates of the same unobserved variable may vary with the technique that we apply. The long-term trend in the level of real GDP or the real exchange rate trend are examples of unobserved variables.

In the context of our course, we use Kalman filtration to estimate the unobserved domestic variables. We will discuss this statistical technique in Module 5.

Elements of the QPM: Trends and Gaps

The two key types of unobservable variables in our QPM are the long-run trends and gaps. This means that we decompose some of the observed variables into “trend” and “gap” components, or, in other words, get estimates of these components. The shocks in our model are going to be estimated as well and such can also be seen as unobserved variables.

In the video below you'll learn about the importance of trends and gaps in the QPM.

[VIDEO M1_5_TRENDS AND GAPS IN THE QPM](#)

Elements of the QPM: Parameters

There are three types of parameters in our model:

1. **The coefficients in model equations:** In the equation for inflation, there is a coefficient which links the marginal costs to inflation. In the equation for output gap, there is a coefficient which defines the simultaneous impact of foreign demand on demand developments in our domestic economy. We will talk more about the equations and coefficients later in this module.
2. **The standard deviations of shocks:** Calibrations of these parameters define which shocks tend to be larger in size. For example, shocks that hit the output gap – the demand shocks or cost push shocks hitting inflation, or others. We will discuss this in modules 4 and 5.
3. **The steady-state parameters:** This set of parameters defines the state to which our economy converges in the long run. We will discuss this when we differentiate between the long-run equilibrium (or trends) in our model and the steady-state.

In the next unit, you will learn about modelling the long-term trends in the QPM and the relationship between what we characterize as the long-term equilibrium in the model and the steady-state parameters.

Steady-State and Modelling Long-Term Trends: Steady State Parameters

The set of steady-state (long-term equilibrium) parameters include:

1. Two inflation targets: domestic and foreign
2. The steady-state level of the real interest rate, both domestic and for the foreign trading partner
3. The rate of change in the real exchange rate
4. The rate of output growth in the steady state

Steady state parameters

| | |
|-------------------------------------|-----------------|
| Domestic inflation target | π^{SS} |
| Foreign long-run inflation (target) | π^{*SS} |
| Domestic real interest rate | r^{SS} |
| Foreign real interest rate | r^{*SS} |
| RER appreciation/depreciation | Δz^{SS} |
| Non-inflationary output growth | Δy^{SS} |

In what follows, we will consider the steady state as the characterization of equilibrium in domestic and foreign economies in a distant future.

In theory, the steady state is often understood as the equilibrium state of an economy that finally converged to a high-income level. For such an economy, the equilibrium rate of growth would be the same as the growth rate for other high-income level economies. In equilibrium, the domestic currency of such an economy should not appreciate or depreciate vis-à-vis other high-income economies. The equilibrium rate of return on investment in such an economy should be the same as the rate of return in other high-income economies and hence the level of the real interest rate should be the same.

In practice, we usually do not assume that the steady-state corresponds to reaching a high-income level. *We think about the steady-state parameters as characterizing equilibrium in 10 or 15 years ahead.* In particular, for developing and emerging economies, it may imply that their steady-state rate of economic growth should be higher than that of high-income economies and steady-state rate of change in the real exchange rate is non-zero.

In the next unit, we will discuss modelling the long-term trends in the QPM and the relationship between what we characterize as the long-term equilibrium in the model and the steady-state parameters

Steady-State and Modelling Long-Term Trends: Long-Term Trends

So far, you've learned that the equilibrium levels of variables – or, in other words, the long-term trends – in this model might change with time. This means that we need to describe the process or provide equations for the long-run trends.

Our simple QPM model does not allow us to impose much economic structure on the equations that describe changes in the long-term trends.

The reason for that is simple: **central banks are primarily interested in analyzing economic developments at a business cycle frequency**. This means that the central bank as an institution effectively implements counter-cyclical policy and focuses on the cyclical as opposed to the long-run dynamics. Therefore, it is crucial to understand and provide structural description for domestic macroeconomic variables and their cyclical dynamics. How variables are interrelated in the long-run is of secondary importance. **Most of the equations for the long-term changes will have a simple autoregressive form.**

There will be a couple of exceptions to this simple representation. In the second week of Module 1, we will talk about the consistency of trends and policy objectives in the long-run. You will see that some variables are interlinked in the long-run perspective in a particular way, consistent with underlying macroeconomic assumptions and therefore admitting some structure.

The equations describing an equilibrium may be set for a long-term value of a variable (level of the long-term trend) or for the rate of the change in the long-term trend. You will also see that the autoregressive equations for trends essentially describe convergence to the steady-state values. In the video below, we will have a look at a couple of examples of how we describe trends in the QPM.

VIDEO M1_6_LONG-TERM TRENDS IN THE QPM

- Long-term (potential) rate of output growth

$$\Delta \bar{y}_t = h_y \Delta \bar{y}_{t-1} + (1 - h_y) \Delta \bar{y}^{SS} + \varepsilon_t^{\bar{y}}$$

- Equilibrium real exchange rate growth

$$\Delta \bar{z}_t = h_z \Delta \bar{z}_{t-1} + (1 - h_z) \Delta \bar{z}^{SS} + \varepsilon_t^{\bar{z}}$$

- Equilibrium real interest rate

$$\bar{r}_t = h_r \bar{r}_{t-1} + (1 - h_r) \bar{r}^{SS} + \varepsilon_t^{\bar{r}}$$

Steady-State and Modelling Long-Term Trends: The Inflation Target

One important variable that defines the equilibrium in the model is, of course, the domestic inflation target. In the model, we describe the inflation target using the following autoregressive process:

$$\pi_t^T = t_1 * \pi_{t-1}^T + (1 - t_1) * \bar{\pi}^{SS} + \varepsilon_t^{\pi^T}$$

In principle, inflation-targeting central banks should not change inflation targets very often. However, central banks in developing and emerging markets may over time revise and gradually reduce the level of the inflation target.

Remember: The bigger the coefficient on the SS, the faster convergence to the SS.

This was, for example, the case of the Czech National Bank in 2010, when the target was reduced from 3 to 2 percent OR of the National bank of Georgia, which reduced the inflation target several times between 2009 and 2017 from 9 to 4 percent.

To account for such instances, we add this equation in our model. The steady-state parameter here defines either an existing inflation target, or a new inflation target, when it is revised for the future period.

Behavioral Equations in the QPM: Aggregate Demand (IS curve)

Now we will introduce the key model equations in the structural form for domestic variables. The following videos explain the two model blocks: Aggregate Demand and Inflation.

[VIDEO M1_7_ AGGREGATE DEMAND \(IS CURVE\)](#)

$$\hat{y}_t = b_1 \hat{y}_{t-1} - b_2 mci_t + b_3 \hat{y}_t^* + \varepsilon_t^y$$

$$mci_t = b_4 \hat{r}_t + (1 - b_4)(-\hat{z}_t)$$

$$r_t = i_t - E_t\{\pi_{t+1}\} \quad z_t = s_t + p_t^* - p_t$$

Let's now look at the equation and the definition of the monetary conditions index together and learn about the macroeconomic motivation and mechanics of this equation.

[VIDEO M1_8_AD EQUATION AND MCI PUT TOGETHER](#)

The positive value of the monetary conditions index (MCI) indicates tight aggregate monetary conditions. Therefore, the coefficient b_2 enters the equation with minus sign.

Real exchange rate gap enters the monetary conditions index with the minus sign. A weaker, in real terms, domestic currency, should stimulate foreign demand for domestic reproduced goods and services. And therefore, it implies more accommodative monetary conditions.

Real Exchange Rate

- Real exchange rate (Z) in levels:

$$Z_t = S_t \frac{P_t^*}{P_t}$$
- where S is nominal exchange rate (LC per unit of FC), P is domestic price level and P* is foreign price level
- Real exchange rate (Z) in logs:

$$z_t = s_t + p_t^* - p_t$$

[VIDEO M1_8_AD EQUATION AND MCI PUT TOGETHER_2](#)

To sum up, low RIR and weaker REER causes accommodative monetary policy while high RIR and appreciated REER causes tight monetary conditions.


Coefficient B2 is usually relatively small and is between 0 and 1. This implies that the pass-through from monetary conditions to demand and output is gradual.

Behavioral Equations in the QPM: Inflation equation (Phillips Curve) in the QPM


The inflation equation in our canonical QPM is written for the headline inflation. It is similar to a Phillips curve equation, which appears in the literature on DSGE models. In the video below, you will learn about the inflation equation.

[VIDEO M1_10_INFLATION EQUATION \(PHILIPS CURVE\)](#)

$$\pi_t = a_1 \pi_{t-1} + (1 - a_1)E\{\pi_{t+1}\} + a_2 rmc_t + \varepsilon_t^\pi$$



Lagged value



Expected value



Real marginal costs

$$rmc_t = a_3 \hat{y}_t + (1 - a_3) \hat{z}_t$$

Output gap

Real exchange rate gap

Now, let's look at the equation for inflation and the definition of the real marginal costs together. The video below explains the macroeconomic motivation of the inflation equation.

[VIDEO M1_11_INFLATION EQUATION AND RMC PUT TOGETHER](#)

$$\uparrow \pi_t = a_1 \pi_{t-1} + (1 - a_1) E\{\pi_{t+1}\} + \overset{0}{\underline{a_2}} rmc_t + \varepsilon_t^\pi$$

$$\uparrow rmc_t = a_3 \hat{y}_t + (1 - a_3) \hat{z}_t$$

Summary

[VIDEO M1_12_SUMMARY](#)

Uncovered Interest Rate Parity (UIP): Uncovered Interest Rate in Theory

In the first part of this module, we studied two of the four key blocks in the domestic part of the QPM: Aggregate Demand and Philips Curve. In this part, we will discuss the two remaining blocks:

1. The Uncovered Interest Rate Parity (or UIP) condition, both with country risk premium and backward-looking behavior
2. The Monetary Policy reaction function, or the interest rate policy rule.

We will also cover the external or foreign block.

To begin, we will start with the concept of the UIP condition in theory and with country risk premium.

VIDEO M1_13_UIP WITH COUNTRY RISK PREMIUM

$$i_t = i_t^* + E_t\{s_{t+1}\} - s_t$$

$$s_t = E_t\{s_{t+1}\} + i_t^* - i_t$$

In equilibrium, an optimizing household (firm) must be indifferent between investing in domestic or foreign assets. The UIP in this simple form does not hold empirically, because domestic and foreign bonds are not always close substitutes, reflecting differences in liquidity and credit risk.

$$s_t = E_t\{s_{t+1}\} + i_t^* - i_t + prem_t$$

Uncovered Interest Rate Parity (UIP): Uncovered Interest Rate Parity with Backward Looking Behavior

The version of the UIP with country risk premium requires a free-floating exchange rate regime, full capital mobility, and fully forward-looking, model-consistent expectations about the exchange rate.

VIDEO M1_14_UIP DEFINITION WITH BACKWARD LOOKING BEHAVIOR

$$s_t = \underbrace{(1 - e_1)}_A E_t\{s_{t+1}\} + \underbrace{e_1}_{\downarrow} [s_{t-1} + 2(\pi_t^r - \bar{\pi}_t^* + \Delta \bar{z}_t)/4] + (i_t^* - i_t + \text{prem}_t)/4 + \varepsilon_t^s$$

Uncovered Interest Rate Parity (UIP): UIP and Exchange Rate Dynamics

[VIDEO M1_15_UIP AND EXCHANGE RATE DYNAMICS](#)

$$s_t = (1 - e_1) E_t\{s_{t+1}\} + e_1 [s_{t-1} + 2(\pi_t^r - \bar{\pi}_t^* + \Delta \bar{z}_t)/4] + (i_t^* - i_t + \text{prem}_t)/4 + \varepsilon_t^s$$

Monetary Policy Reaction Function (Policy Rule): Taylor Rule

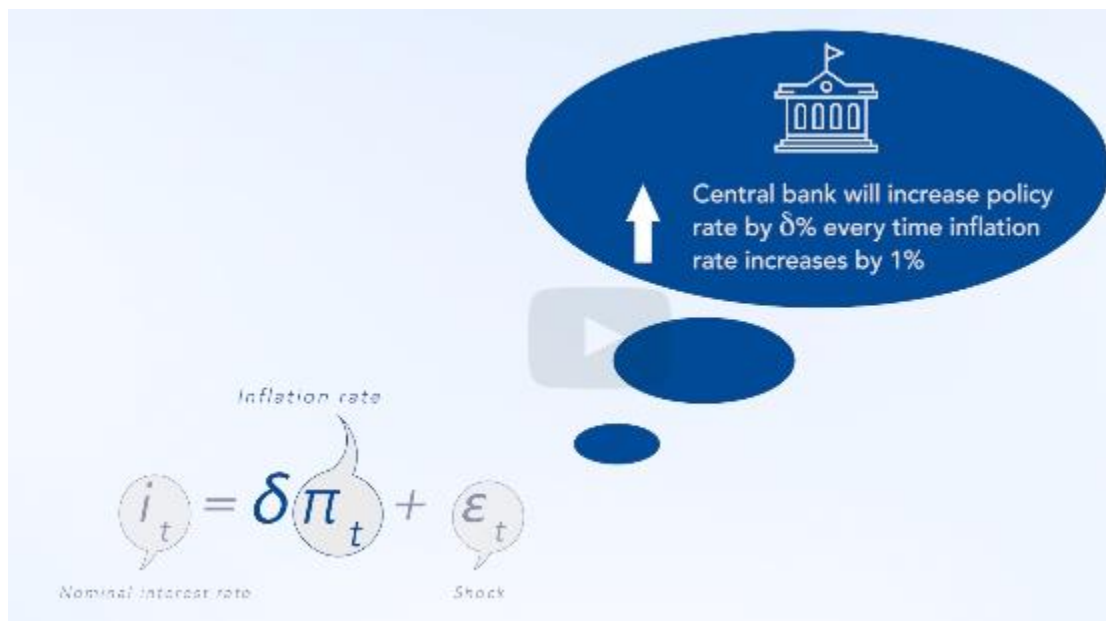
There are four key variables in the model; the output gap, nominal interest rate, rate of inflation, and nominal exchange rate. All other variables in the model are either exogenous or can be obtained from identities containing these four variables.

With three equations and four variables, the model still is not completed. We need a fourth equation to complete the model.

The fourth equation is the monetary policy rule. In our canonical model, **we assume that the central bank controls the interest rate**. The monetary policy rule describes how the central bank should change the nominal interest rate in response to specific economic conditions; for example, inflation.

The monetary policy rule is a condition required to close the model and ensure a unique equilibrium. This means that the rule must ensure that the reaction of the central bank can steer the economy back to equilibrium whenever it's thrown off the equilibrium; by a shock, for example.

[VIDEO M1_16_TAYLOR RULE](#)



The monetary policy rule must satisfy one condition to ensure a unique equilibrium. **Delta to be higher than 1 (Taylor principle)**. It states that whenever inflation moves by 1%, the interest rate must move in the same direction by more than 1%.

So this is how the Taylor Principle works: the reaction of the monetary policy to inflation has to be strong enough to make the real interest rate follow the same direction of change as the nominal interest rate, so that the central bank can have a stabilizing effect on inflation and ensure a well-defined equilibrium for the system.

VIDEO M1_17_OTHER MONETARY POLICY RULES

$$i_t = \delta_{\pi} E_t[\pi_{t+1}] + \delta_y \hat{y}_t + \varepsilon_t$$

Monetary Policy Reaction Function (Policy Rule): Interest Rate Policy Rule

VIDEO M1_18_INTEREST RATE POLICY RULE

•The IR rule in the model:

$$i_t = g_1 i_{t-1} + (1-g_1) \{ i_t^n + g_2 (E_t[\pi_{t+N}^4] - \pi_{t+N}^T) + g_3 \hat{y}_t \} + \varepsilon_t$$

The diagram illustrates the components of the IR rule equation. Arrows point from boxes below to the corresponding terms in the equation:

- Smoothing Component** points to $g_1 i_{t-1}$.
- Neutral interest rate** points to i_t^n .
- Deviation of expected inflation from the target** points to $g_2 (E_t[\pi_{t+N}^4] - \pi_{t+N}^T)$.
- Output gap** points to $g_3 \hat{y}_t$.
- Monetary Policy Shock** points to ε_t .

$$i_t^n = \bar{r}_t + E_t[\pi_{t+N}^4]$$

The equation shows the neutral interest rate i_t^n as the sum of the real rate \bar{r}_t and the expected inflation $E_t[\pi_{t+N}^4]$. A red checkmark is placed under \bar{r}_t and a red underline is placed under $E_t[\pi_{t+N}^4]$.

The neutral interest rate represents the level of the IR that is consistent with the economy operating on its potential and inflation on the target.

Foreign Block in the Model: Variables in Foreign Block

Unlike in the domestic part of the model, there is no economic structure (or economic interpretation) in the foreign block. All variables in the foreign or external block follow simple, auto regressive processes:

Foreign output gap:

$$\hat{y}_t^* = \rho_{\hat{y}^*} \hat{y}_{t-1}^* + \varepsilon_t^{\hat{y}^*}$$

Foreign nominal interest rate:

$$i_t^* = \rho_{i^*} i_{t-1}^* + (1 - \rho_{i^*})(\bar{r}_t^* + \pi_t^*) + \varepsilon_t^{i^*}$$

Foreign real interest rate:

$$r_t^* = i_t^* - \pi_t^*$$

Foreign natural (trend) real interest rate:

$$\bar{r}_t^* = \rho_{\bar{r}^*} \bar{r}_{t-1}^* + (1 - \rho_{\bar{r}^*}) \bar{r}^{*SS} + \varepsilon_t^{\bar{r}^*}$$

Foreign real interest rate gap:

$$\hat{r}_t^* = r_t^* - \bar{r}_t^*$$

Foreign inflation rate:

$$\pi_t^* = \rho_{\pi^*} \pi_{t-1}^* + (1 - \rho_{\pi^*}) \pi^{*SS} + \varepsilon_t^{\pi^*}$$

There is one exception in the variables: the equation for the foreign nominal interest rate. This equation shows an endogenous reaction to the foreign inflation and equilibrium real interest rate. Since these two variables are themselves exogenous, the foreign interest rate follows a de facto exogenous path as well.

The exogeneity of the foreign block means that it will never be affected by developments in the domestic economy. However, the opposite is not true. Foreign variables will affect the small open domestic economy through the Aggregate Demand (foreign output gap and foreign inflation in MCI), Inflation (foreign inflation rate in RMC), UIP (foreign interest rate), and the purchasing power parity (PPP) condition (foreign inflation rate) which will be discussed in the next unit.

Purchasing Power Parity and Real Exchange Rate: Purchasing Power Parity Definition

The QPM is sometimes called a gap model. This means that it treats some variables in deviation from their long-term equilibrium values, or trends. So it is necessary to separate cycles from trends for such variables.

The trends are treated as exogenous to monetary policy, as the natural or equilibrium trajectory of variables in the absence of shocks.

Exogeneity means that monetary policy cannot influence trends. However, we still need to estimate these trends and ensure that they are mutually consistent with policy objectives and treated consistently with them. The first instance where the need for such consistency appears is in the so-called Purchasing Power Parity (PPP) condition.

VIDEO M1_19_ABSOLUTE VERSION OF THE PPP

The PPP, just like the UIP, is a non-arbitrage condition. It states that the price of goods should be the same in two different markets, once expressed in the same currency. In its simplest and absolute version, the PPP condition can be represented by this equation:

$$P = S P^*$$

. In practice, there are some problems with this formula. First, empirically, price levels do not equate in the long run for a variety of reasons that prevent agents from exploiting arbitrage gains. In practice, the higher the level of GDP per capita is in more advanced countries, for example the higher the level of prices. Second, the notion of a single price level representing a basket of goods is problematic where the level is somewhat arbitrary. To circumvent these difficulties, it is better to work with the changing prices. That's why we use a weaker version of the PPP, a relative version.

Purchasing Power Parity and Real Exchange Rate: Relative Version of the Purchasing Power Parity

VIDEO M1_20_RELATIVE VERSION OF THE PPP

$$\pi = \Delta S + \pi^*$$

$$\Delta S = \pi - \pi^*$$

The relative PPP, like the absolute PPP, suffers from the distortions that prevent perfect exploitation of arbitrage gains. This implies that it also cannot be applied in practice. Essentially, in practice, we also don't see that this equation holds. To resolve the issue, we have to include a wedge to make the equation hold all the time.

$$\Delta z_t = \Delta S_t + \pi_t^* - \pi_t$$

A wedge that we call real exchange rate. Now, in the relative version, the wedge becomes the rate of change of the real exchange rate, which is here, delta z. That means it is the real exchange rate depreciation.

Implications for Monetary Policy Objectives: Implications of Real Exchange Rate

VIDEO M1_21 IMPLICATIONS OF REAL EXCHANGE RATE

The PPP condition, modified by the time-varying wedge (REER) that captures changes in the real exchange rate, must be also satisfied in the long term. But we know that it is always satisfied because we are forcing it, using the wedge. Let's consider the wedge modified relative PPP with the relevant variables measured at their trend, or long-term equilibrium levels.

$$\Delta \bar{z}_t = \Delta \bar{s}_t + \bar{\pi}_t^* - \pi_t^T$$

Assume that domestic policy makers want to set a target for inflation. If their choice is credible, that is, if policy makers can commit to bringing inflation back to the target, then the long run average inflation will be the target itself. Always remember that trends are treated as exogenous to monetary policy. They can be, however, the result of choosing a policy framework.

Among all the four variables in the relative PPP, domestic policy makers may have control over two of them - delta s bar and inflation target. But the policy makers can pick either delta s bar or inflation target. They cannot pick both at the same time. This is because policy makers do not have any control over the real exchange rate in the long term. They can affect it in the short term, but not in the long term. They also don't have control over foreign inflation rate. Therefore, if two of the four variables are not under the control of the policy makers, when they pick one of the two variables, delta s bar or inflation target, which are under their control, the other becomes implicitly determined because the PPP must hold at all times.

Real Exchange Rate and Interest Rate in the Long-Run: UIP in the Long-Run

VIDEO M1_22 UIP IN THE LONG RUN

The forward looking UIP condition that we discussed earlier was written in nominal terms.

$$s_t = E_t \{ s_{t+1} \} + (i_t^* - i_t + prem_t)$$

But it can be written also in the real terms by adding and subtracting both domestic and foreign inflation on both sides of the equation.

$$z_t = E_t \{ z_{t+1} \} + (r_t^* - r_t + prem_t)$$

So the expected rate of depreciation of the real exchange rate is equal to the expected rate of depreciation of the nominal exchange rate plus the differential between inflation abroad and domestic inflation.

$$E_t\{z_{t+1}\} - z_t = E_t\{s_{t+1}\} - s_t + E_t\{\pi_{t+1}^*\} - E_t\{\pi_{t+1}\}$$

Another term that is important to define is the real interest rate, both foreign and domestic.

$$r_t = i_t - E_t\{\pi_{t+1}\}$$

$$r_t^* = i_t^* - E_t\{\pi_{t+1}^*\}$$

Finally, we gain the REER depreciation in the long term as:

$$\Delta \bar{z}_{t+1} = \bar{r}_t - \bar{r}_t^* - prem_t$$

Summary

[VIDEO M1_23_SUMMARY](#)

There are four key equations in the QPM:

- 1) The aggregate demand, which relates the economic activity (measured by the output gap) to monetary conditions and foreign demand (measured by the output gap in the trading partner)
- 2) The Phillips curve, which describes how inflation reacts to expected inflation and real marginal costs
- 3) The UIP condition, which establishes a non-arbitrage condition between investing in domestic and foreign assets
- 4) The monetary policy rule, which captures how the central bank reacts by changing the nominal interest rate in response to deviations of inflation from its target and to the output gap

QPM modeling - Modul 2

VIDEO M2_1_ABOUT MODUL 2

Principles of Variable Naming Convention

Here are some basic variable names that will help you navigate the model file in IRIS better:

Legend for basic variable names

| | |
|--------------------|--|
| • <i>CPI</i> | CPI (index) |
| • <i>GDP</i> | Real GDP Level (index) |
| • <i>S</i> | Nominal Exchange Rate (LCY per 1 FCY) |
| • <i>Z</i> | Real Exchange Rate (index) |
| • <i>RS</i> | Nominal (Policy) Interest Rate (% p.a.) |
| • <i>RR</i> | Real Interest Rate (% p.a.) |
| • <i>RSNEUTRAL</i> | Nominal Neutral Interest Rate (% p.a.) |
| • <i>PREM</i> | UIP (Risk) Premium (% p.a.) |
| • <i>MCI</i> | Real M onetary C onditions I ndex (%) |
| • <i>RMC</i> | Real M arginal C ost (%) |

Canonical QPM is a dynamic model. This means that it describes development of an economy over time and all the variables are time-dependent. Therefore, we need to be able to specify the timing of the variables when coding the model. In IRIS, the timing of a non-contemporaneous variable is specified as a number in curly braces after the variable's name. For example, `L_GDP_GAP{-1}`.

A negative number indicates a lag of a variable. A positive number indicates a lead. The number itself specifies periods backwards or ahead. For instance, a `{-1}` means that we are referring to the one-period lag of a variable, while `{+1}` (or just `{1}`) means a one-period lead/expectation. If the variable is not succeeded by the curly braces, it means that the variable is contemporary.

Learning activity 1

0 points possible (ungraded)

Code the following analytical equations using the mnemonics described above: (You do not need to click Submit but can see a solution after you have attempted this activity by clicking Show Answer)

1) Fisher equation, which determines the relationship between nominal interest rate i_t , real interest rate r_t , and expected year-on-year (yoy) inflation $E_t [\pi_{t+1}^A]$.

$$r_t = i_t - E_t [\pi_{t+1}^A]$$

2) Real exchange rate in log-linearized form z_t is equal to the sum of nominal exchange rate s_t and foreign price index p_t^* minus domestic price index p_t .

$$z_t = s_t + p_t^* - p_t$$

3) Nominal neutral interest rate $i_t^{neutral}$ is equal to the sum of equilibrium (or trend) real interest rate \bar{r}_t and expected inflation $E_t [\pi_{t+1}^A]$.

$$i_t^{neutral} = \bar{r}_t + E_t [\pi_{t+1}^A]$$

4) AR(1) process for real exchange rate trend depreciation.

$$\Delta \bar{z}_t = \rho^{\Delta \bar{z}} \cdot \Delta \bar{z}_{t-1} + (1 - \rho^{\Delta \bar{z}}) \cdot \Delta \bar{z}_{ss} + \varepsilon_t^{\Delta \bar{z}}$$

- Fisher equation

$$RR = RS - D4L_CPI\{+1\};$$

- Definition of Real Exchange Rate (RER)

$$L_Z = L_S + L_CPI_RW - L_CPI;$$

- Neutral nominal interest rate

$$RSNEUTRAL = RR_BAR + D4L_CPI\{+1\};$$

- Equilibrium RER depreciation

$$DLA_Z_BAR = rho_DLA_Z_BAR * DLA_Z_BAR\{-1\} \dots$$

[VIDEO M2_2_VISUALIZING THE PROCESS OF CREATING A MODEL IN IRIS](#)

MATLAB is a licensed stand-alone software created by Mathworks, which includes user interface, computing capabilities, a large set of standard functions, methods, and objects, etc.

IRIS is a specialized econometric modelling and forecasting toolbox, developed by one of the IMF's former employees, to be used in the MATLAB environment. IRIS allows us to work with time series objects, model objects, report objects, etc. IRIS is not a stand-alone software, so it cannot be run independently of MATLAB. IRIS is an open-source toolbox, which means that it can be downloaded for free. IRIS is just one of many toolboxes that we can use with Matlab.

VIDEO M2_3_CREATING A MODEL STRUCTURE IN IRIS

We need to create the model.model text file. You will create an empty text file for the model.

First, we will start with transitions equations and its elements (variables, parameters, and shocks). Each of these types have its own dedicated block in the IRIS model file.

!transition_equations

!transition_variables

!parameters

!transition_shocks

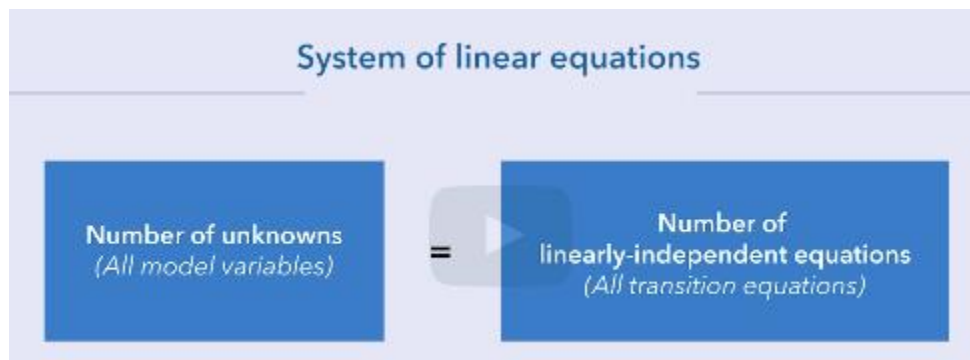
However, if we wanted to put the model on the data, we wouldn't be able to do it using only these four blocks. We need to specify two additional very important blocks in model.model, which would allow us to introduce a bridge between the analytical model and data.

!measurement_variables

!measurement_equations

VIDEO M2_4_NUMBER OF VARIABLES AND EQUATIONS IN THE MODEL

It is important to have the same number of transition variables and equations in the model. Simply said, every variable must have its own equation.



It also requires that all equations are linearly independent.

To build the QPM, we first need to specify the four building blocks: IS curve, Phillips curve, Taylor rule, and UIP condition. In the video below, we start with the IS curve, which describes the dynamics of the output gap:

$$\hat{y}_t = b_1 * \hat{y}_{t-1} - b_2 * mci_t + b_3 * \hat{y}_t^* + \varepsilon_t^{\hat{y}}$$
$$mci_t = b_4 * \hat{r}_t + (1 - b_4) * (-\hat{z}_t)$$

VIDEO M2_5_CODING THE IS CURVE IN MATLABIRIS

Notes: DO NOT declare lags and leads variables as separate variables in !Transition variables

```
gpm.xml x model.model x
1 !transition_variables
2 L_GDP_GAP
3 MCI
4 L_GDP_RW_GAP
5 RR_GAP
6 L_Z_GAP
7
8 !transition_shocks
9 SHK_L_GDP_GAP
10
11 !parameters
12 b1
13 b2
14 b3
15 b4
16
17 !transition_equations
18 L_GDP_GAP = b1*L_GDP_GAP{-1} - b2*MCI + b3*L_GDP_RW_GAP + SHK_L_GDP_GAP;
19 MCI = b4*RR_GAP + (1-b4)*(-L_Z_GAP);
20
21 !measurement_variables
22
23 !measurement_equations
24
```

For now, we have boiled 2 equations, but we have 5 !transition_variables. It means that our model is not complete.

But first, we need to fill in also the measurement section. We are building a bridge between analytical model and data. The output gap is unobserved variable, but we can observe by statistical methods the output (GDP). But we must have here also the measurement equations for the measurement variables. And because we create OBS_L_GDP from L_GDP, we need to have this variable also in !transition_variables section.

```
gpm.xml x model.model x
1 !transition_variables
2 L_GDP_GAP
3 MCI
4 L_GDP_RW_GAP
5 RR_GAP
6 L_Z_GAP
7 L_GDP
8 L_GDP_BAR
9
10 !transition_shocks
11 SHK_L_GDP_GAP
12
13 !parameters
14 b1
15 b2
16 b3
17 b4
18
19 !transition_equations
20 L_GDP_GAP = b1*L_GDP_GAP{-1} - b2*MCI + b3*L_GDP_RW_GAP + SHK_L_GDP_GAP;
21 MCI = b4*RR_GAP + (1-b4)*(-L_Z_GAP);
22 L_GDP = L_GDP_GAP + L_GDP_BAR;
23
24 !measurement_variables
25 OBS_L_GDP
26
27 !measurement_equations
28 OBS_L_GDP = L_GDP;
```

In the video below, we will code the Phillips curve, which describes the dynamics of inflation:

$$\pi_t = a_1 * \pi_{t-1} + (1 - a_1) * (E_t [\pi_{t+1}]) + a_2 * rmc_t + \varepsilon_t^\pi$$

$$rmc_t = a_3 * \hat{y}_t + (1 - a_3) * \hat{z}_t$$

$$\pi_{t+1}^e = E_t [\pi_{t+1}]$$

VIDEO M2_6_CODING THE PHILLIPS CURVE IN MATLABIRIS

Producers maximize their profits by setting prices that are Calvo-sticky (random) in a monopolistic competition environment facing variable real marginal costs (RMC). RMC of the producers are estimated by a combination of the output gap to approximate cost of domestically produced inputs and real exchange rate gap to approximate costs of imported inputs.

So far you have learned to codify the dynamics of aggregate demand (IS curve) and inflation (Phillips curve). In the next video, we will add the monetary policy reaction function, or the so-called modified Taylor rule.

$$i_t = g_1 * i_{t-1} + (1 - g_1) * (i_t^{neutral} + g_2 * (E_t [\pi_{t+4}^A] - E_t [\pi_{t+4}^{TAR}]) + g_3 * \hat{y}_t) + \varepsilon_t^i$$

$$i_t^{neutral} = \bar{r}_t + E_t [\pi_{t+1}^A]$$

VIDEO M2_7_CODING THE TAYLOR RULE

Now, we will add the monetary policy reaction function. The central bank's preference for the corresponding parameters G2 and G3 would determine the famous inflation output tradeoff. Parameter G1 measures the preference of the monetary authority for smooth policy rate. Usually, the CB don't like changing the policy rate rapidly. They are concerned about uncertainty such rapid changes might have on the financial system. Sometimes, the CB prefer smooth rates because they are not independent enough, for example, from fiscal pressures and are thus prevented from conducting a more proactive monetary policy.

Neutral rate is estimated policy rate consistent with the economy operating at full capacity and stable inflation.

Now we will codify the **UIP condition**, which describes the behavior of the nominal exchange rate:

$$s_t = (1 - e_1) * (E_t [s_{t+1}]) + e_1 * \left(s_{t-1} + \frac{2}{4} * (\pi_t^{TAR} - \bar{\pi}_t^* + \Delta \bar{z}_t) \right) + \frac{-i_t + i_t^* + prem_t}{4} + \varepsilon_t^s$$

VIDEO M2_8_CODING THE UIP CONDITION

We have to add some explicit external sector flavor to our model. We are already working with some external sector variables in the model (foreign output gap, or real exchange rate gap). However, the model is still far

a domestic one. Therefore, we will introduce an equation determining nominal exchange rate (modified UIP condition).

UIP stands for Uncovered Interest Rate Parity. It is a no-arbitrage condition under which investors would be indifferent between investing into IR in two countries. It is modified because in its pure form, the UIP doesn't hold empirically in the short term. And finally, it is uncovered because we don't use an explicit forward exchange rate contract to hedge or cover out exposure to exchange rate risks. Rather, we use expectations of the exchange rate instead.

Coding Trends

Before we proceed with the coding, let's revisit the standard structure for a typical stationary trend process from Module 1:

$$\bar{X}_t = \alpha * \bar{X}_{t-1} + (1 - \alpha) * \bar{X}_{ss} + \varepsilon_t^{\bar{X}}$$

where \bar{X}_t is a stationary variable (which in the context of our model means that it's either a trend growth rate of the underlying non-stationary variable, or a trend real interest rate), and \bar{X}_{ss} is its steady state value.

Most of the trends in the model would follow this type of generic AR(1) process, with one exception which we will discuss separately. **The trends that follow the generic process are called exogenous trends**, because they are not affected directly by any variable in the model. This means that their dynamics depend only on the realization of the corresponding shock. **All other trends (only one in the case of current model) are called endogenous.**

VIDEO M2_9_CODING TRENDS

There are six trend variables in our simple model:

- 1) real GDP trend,
- 2) inflation target,
- 3) real exchange rate trend,
- 4) domestic real interest rate trend,
- 5) foreign real interest rate trend,
- 6) and long term UIP premium.

Real GDP trend – it is non-stationary variable (it is growing in the steady state). Therefore, we are adding a trend process to the growth rate of GDP trend, not to the level.

$$\bar{X}_t = \alpha \bar{X}_{t-1} + (1 - \alpha) \bar{X}_{ss} + \varepsilon_t^{\bar{X}}$$

GDP trend

Inflation target – it features in the monetary policy reaction function. Inflation target is a stationary variable, converging to the calibrated constant value of the steady state.

$$\bar{X}_t = \alpha \bar{X}_{t-1} + (1 - \alpha) \bar{X}_{ss} + \varepsilon_t^{\bar{X}}$$

Inflation target

VIDEO M2_10_CONSISTENCY OF TRENDS

The remaining 4 trends will be modelled as follows: 3 exogenous following the generic process and 1 endogenous that will be determined by the 3 exogenous in the condition called consistency of trends. In general, we have some flexibility to choose which one will be endogenous.

Foreign real interest rate trend – always exogenous as we have no control over that.

Exogenous Foreign RIR trend: RR_RW_BAR

So now we are left with 3 trends: RR_BAR, DLA_Z_BAR, PREM. One of them must be endogenous. In general, we can choose which one will be endogenous but finally, we will find out that **L_Z_BAR is always exogenous.**

Exogenous DLA_Z_BAR

To say if endogenous variable will be PREMIUM or RR_BAR is not straightforward. The motivation for choosing either of them vary, but mostly have to do with the desired volatility of the variable (you have a direct control over the trend through its shock), a better idea about its historical dynamics, or better sense of its steady state value. We will model the RR_BAR as exogenous and PREMIUM as endogenous.

RR_BAR exogenous

Premium – is endogenous. For the premium, we apply the consistency of trend condition. You may notice that this is nothing else but the long-term version of the UIP condition. Note that it is still a modified version of the UIP condition as it is adjusted by the premium. But it is closer to the pure form of the UIP condition as we do not have shock here.

$$\text{PREM} = \text{RR_BAR} - (\text{RR_RW_BAR} + \text{DLA_Z_BAR}_{t+1});$$

Now we have 26 transition variables and 23 transition equations!

Coding External Sector

Almost all the equations, except for some identities, are stand-alone AR(1) processes, converging to their respective steady states. By exogenous we mean that the domestic variables will not influence any of the foreign variables, and the dynamics of the foreign variables will be determined fully by the foreign sector shocks.

VIDEO M2_11_MODELING EXTERNAL SECTOR

It contains variables that we have used in the equations already:

- 1) Foreign output gap
- 2) Foreign inflation
- 3) Foreign nominal interest rate
- 4) Foreign real interest rate (already defined)

VIDEO M2_12_WRAPPING UP MODEL.MODEL

Working with model.model in IRIS

In this unit, we will cover the basic IRIS commands that will allow us: (i) to transform the model from the text format into an IRIS object; (ii) solve the model for steady states; and (iii) extract other useful information from the IRIS model object, for example the names and descriptions of variables, steady state values, lists of equations, etc.

IRIS commands:

model

solve

sstate

get

To solve the model, we will have to calibrate it first. Calibration consists of assigning values to all parameters in the model. In this module, we use a pre-set calibration. There are two main points regarding the calibration of model parameters:

- 1) To make reading the model easier, we chose to calibrate all the model parameters, except for selected steady state parameters, to positive numbers. This means that if one variable has a negative impact on the other (for example, MCI negatively affects the output gap), then the respective coefficient will be preceded by a minus sign in the equation.
- 2) To ensure the stability of the model, most of the coefficients in the model equations will be between 0 and 1.

VIDEO M2_13_SOLVING MODEL.MODEL

In the file readmodel.m there is a MATLAB predefined function called function with the output (m – model object, p – parameters, mss – model steady states) and input (empty) defined.

Debugging Error Messages in MATLAB

When working in MATLAB/IRIS environment, you will usually encounter two broad types of error messages: **Matlab-specific errors** or **IRIS-specific errors**.

IRIS-specific errors will have a special announcement that distinguishes them from Matlab-specific errors. These errors contain a line saying, “**IRIS Toolbox Error**”. Although all errors that we cover in this section are IRIS-specific and related to debugging the model file, we also discuss general principles of debugging the errors; these apply equally to Matlab-specific errors, too.

VIDEO M2_14_READING AND DEBUGGING MATLAB ERRORS

| Error | Error message | Example of IRIS command which replicates the error |
|--|--|--|
| Wrong order of input arguments | <pre>IRIS Toolbox Error @iris:passvalopt. Incorrect list of user options</pre> | <pre>m=model('linear=',true, 'model.model')</pre> <p>To check the order of input arguments of an IRIS function, type 'help [function name]' in Command Window</p> |
| No value assigned to the last input option | <pre>IRIS Toolbox Error @iris:passvalopt. *** No value assigned to the last option: '{name_of_option}'.</pre> | <pre>m=model('model.model', 'linear=')</pre> <p>There is no value assigned to option 'linear=', which is the last option specified in the command [model].</p> |
| Wrong values of input options | <pre>IRIS Toolbox Error @iris:passvalopt. Value assigned to option {name_of_option} fails validation: '{validation_criteria}'</pre> | <pre>m=model('model.model', 'linear=',1)</pre> <p>The IRIS error message will tell you that the value assigned to option 'linear=' is not in the format it expects it to be, i.e. IRIS expects a Boolean (logical) input ("true" or "false"), while the supplied value is a scalar (1 in this example).</p> <pre>p = struct(); m=model('model.model', 'linear=', 'assign', p)</pre> <p>Here, IRIS again expects a Boolean input after option 'linear=', but instead gets a string ('assign').</p> |

VIDEO M2_15_UNDECLARED OR MISTYPED NAMES

VIDEO M2_16_SYNTAX ERRORS

VIDEO M2_17_NUMBER OF VARIABLES NOT MATCHING NUMBER OF EQUATIONS



Fundamental equations

- IS Curve
- UIP Condition
- Phillips Curve
- MP Reaction Function

Definitions and identities

- Equations for growth rates
- RMC
- MCI
- Decomposition into gap and trend



Exogenous equations

- Foreign block equations
- AR(1) equations

Important economic relationships

- Definition of Real Exchange Rate
- Fisher Equation
- Neutral Interest Rate
- Long-term version of UIP



VIDEO M2_18_PARAMETER VALUE IS NOT ASSIGNED

VIDEO M2_19_SUMMARY

QPM modeling - Modul 3

VIDEO M3_1_ABOUT MODUL 3

Checking Model Properties: What and Why?

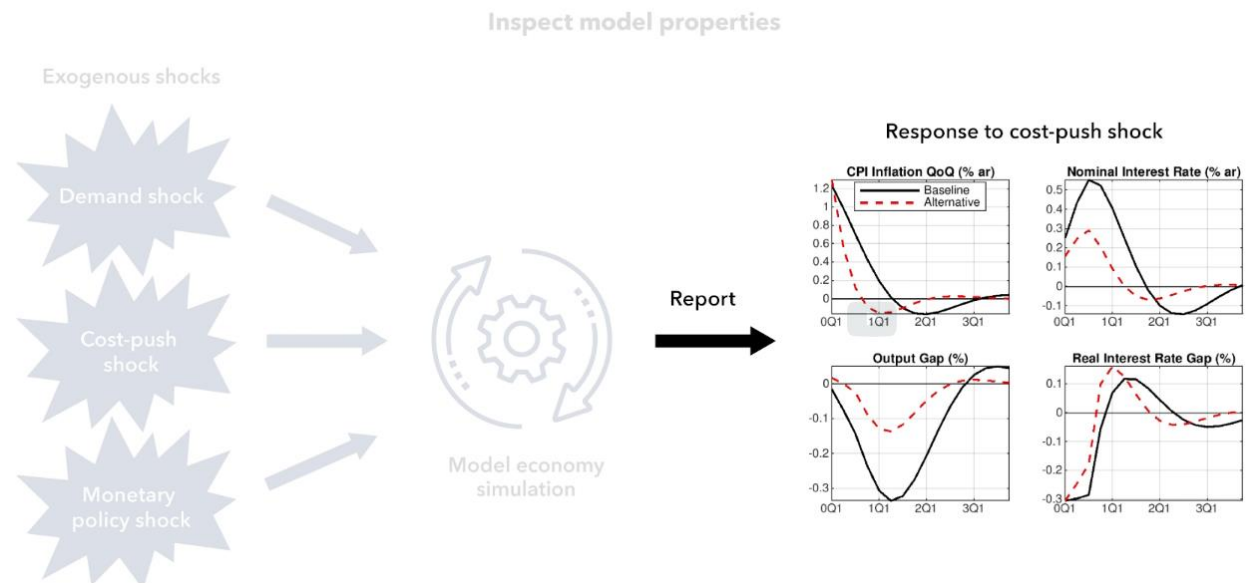
Before using the QPM for forecasting and policy analysis, we must make sure that its behavior conforms to our intuition and empirical evidence about economic relationships in our country. In other words, we need to check the **properties of the calibrated model**.

What do we mean by checking model properties?

In this course, checking model properties refers to examining the model economy's response to typical shocks. For example, what is the predicted reaction of GDP and inflation after a fiscal stimulus? Or how much do macro variables change in the QPM after an increase in world oil prices? These questions are very hard to answer based on individual model equations, because these questions address the model's behavior **as a whole**, accounting for all the complex interactions between variables. A useful graphical tool to summarize these model responses are Impulse Response Functions.

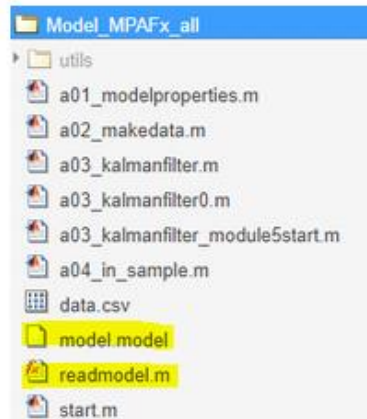
Why is it important to carefully inspect model properties?

Because the model forecast must reflect the forecasting team's view of the economy and the transmission mechanism. As you progress in the course, you will realize that the QPM is just a tool to anchor the forecasting and policy analysis process. In practice, models do not produce the forecast, economists do. And the economists must be able to explain their forecast to the decision makers and the public.



VIDEO M3_2_HOUSEKEEPING AND LOADING THE MODEL

Quick Revision of model.model and readmodel.m files



The **model.model** file describes all the variables and equations in our QPM, similar to how we would write them on paper. This file lays out the model structure in a very general form, without assigning specific values to the parameters.

For example, we can see in the model.model file that inflation depends on the output gap through the Phillips Curve, but we do not get a quantitative sense for the strength of this relationship.

```
a01_modelproperties.m x model.model x +
96
97 %% --- Inflation (the Phillips curve) ---
98 DLA_CPI = a1*DLA_CPI{-1} + (1-a1)*DLA_CPI{+1} + a2*RMC + SHR_DLA_CPI;
99
100 %-- Real marginal cost
101 RMC = a3*L_GDP_GAP + (1-a3)*L_Z_GAP;
...
```

This quantitative information is provided in the **readmodel.m** file, which assigns specific numerical values to the parameters.

For example, the parameterization in the readmodel.m tells us that "all else equal", a 1pp higher output gap is associated with 0.14 pp higher inflation in a given quarter. Besides assigning parameter values, this program also finds the rational expectations solution of the model and calculates its steady state. When we call this function with the syntax **[m,p,mss] = readmodel()**, the solved model will be returned in object 'm', while the parameters and steady state values will be placed in the structures 'p' and 'mss'.

```
a01_modelproperties.m x model.model x readmodel.m x +
41 %----- 2. Inflation equation (the Phillips curve)
42 % DLA_CPI = a1*DLA_CPI{-1} + (1-a1)*DLA_CPI{+1} + a2*RMC + SHR_DLA_CPI;
43 % RMC = a3*L_GDP_GAP + (1-a3)*L_Z_GAP;
44
45 % inflation persistence;
46 p.a1 = 0.7; % a1 varies between 0.4 (low persistence) to 0.9 (high persistence)
47
48 % passthrough of marginal costs to inflation (the impact of rmc on inflation)
49 p.a2 = 0.2; % a2 varies between 0.1 (a flat Phillips curve and a high sacrifice ratio) and 1.0
50
51 % the ratio of domestic costs in firms' aggregate costs
52 p.a3 = 0.7; % a3 varies between 0.9 (for a relatively more closed economy) and 1.0
53
```

Specifying Shocks for the IRFs

VIDEO M3_3_SPECIFYING SHOCKS

Simulating Model Responses to Shocks

VIDEO M3_4_SIMULATING IRFs

`s = simulate(m, d, range, 'deviation', [true/false])`

Input:

`m` - Solved model object

`d` - Database with initial conditions and shocks

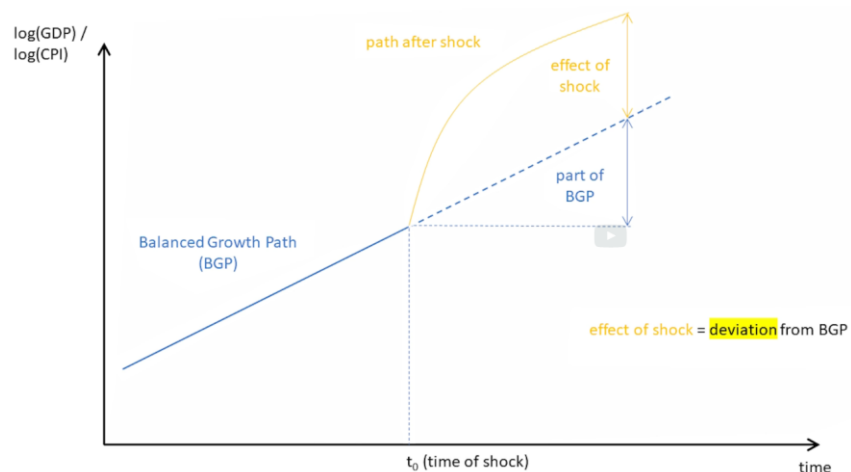
`range` - Simulation range

Option:

`'deviation'` = [true/false] - Treat input and output data as deviations from balanced growth path

Revision: Balanced Growth Path

In the video you learned about the concept of the Balanced Growth Path (BGP). To measure the true **impact of a shock**, we often want to show the path of model variables as **deviations from the BGP**. This is a very important concept, so make sure you understand it before moving to the next unit.



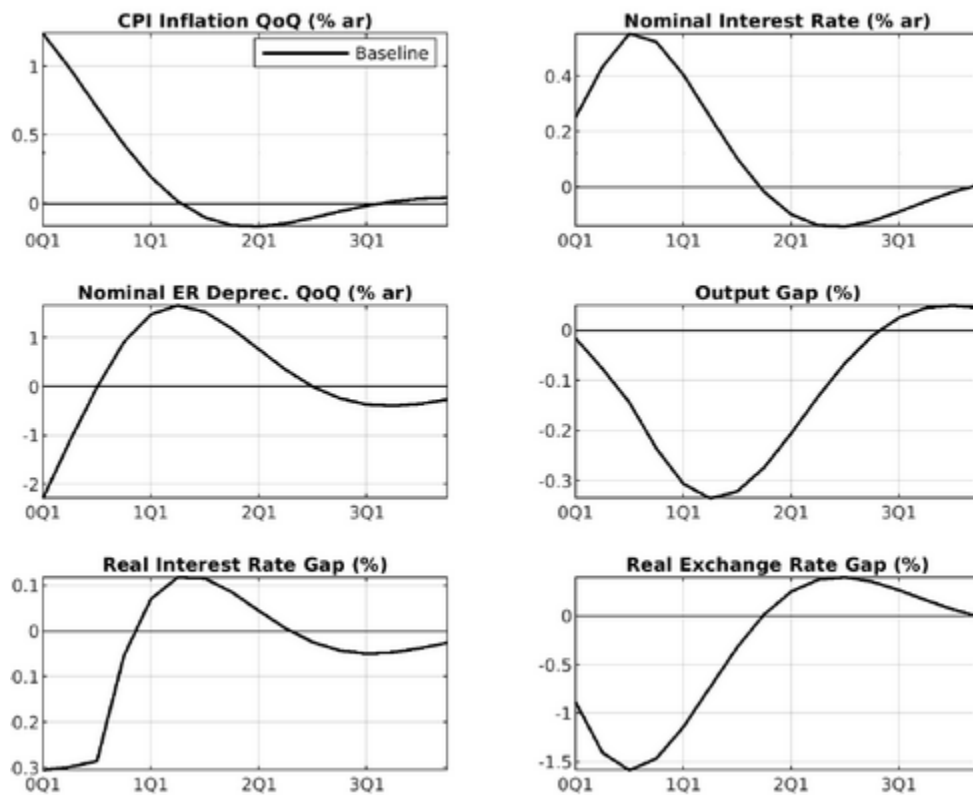
Creating Reports with Impulse Response Functions (IRFs)

[VIDEO M3_5_GENERATING A REPORT WITH IRFS](#)

Tweaking the Code

If you open the Shocks.pdf file, you will find one titled page for each shock that contains the responses of six selected macro variables.

Inflationary (cost-push) Shock



However, before scrutinizing these IRFs, let's do a quick exercise to reinforce our understanding of the program code. Think about the following questions:

1. How could we add an extra page to 'Shocks.pdf' which shows the model's response to an unexpected monetary policy tightening of 100 basis points?
2. How could we add an extra graph to each page that shows the response of the Real Monetary Condition Index?

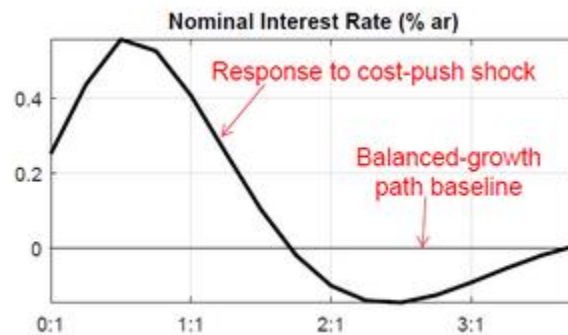
Try to do these modifications in the program code on your own. If you get stuck or just want to compare your solution with mine, watch the following videos.

[VIDEO M3_6_ADDING NEW SHOCK](#)

[VIDEO M3_7_ADDING NEW GRAPH](#)

General Interpretation of an IRF

In this section, we will cover the interpretation of the Impulse Response Functions (IRFs) in the **Shocks.pdf**. These IRFs are extremely useful to explain and better understand the transmission mechanisms embedded in the canonical QPM.



How should we read the graphs in the Shocks.pdf?

Recall that we start the model from the steady state. At the very first simulation point an unexpected shock is realized. The shock is not persistent, as it lasts only for one quarter. However, due to rigidities and frictions in the model, it takes time for the economy to fully adjust.

On the graph, the thick black impulse response line shows the impact of the shock over time compared to the counterfactual of no shock. The no shock baseline is represented with a straight line at zero. As we discussed, this does not mean that the value of the variable would have been zero in the absence of the shock. What we see on the graph is the deviation from the balanced-growth path.

For example, this IRF shows that in the third quarter after a cost-push shock the nominal interest rate is nearly 0.6 percentage points above what it would have been otherwise. Over time the nominal interest rate returns to the neutral level that is determined by the steady state real interest rate and the inflation target.

Model Responses to Cost-Push and Demand Shocks

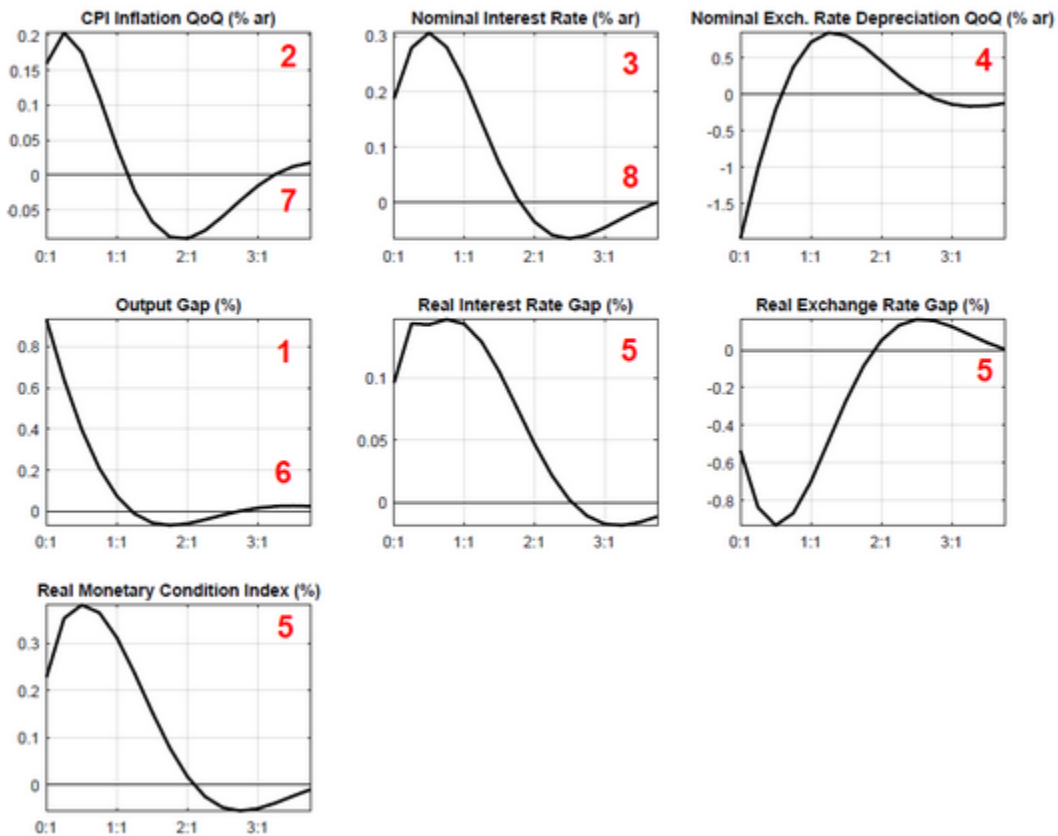
Now let's trace the effects of two fundamental shocks in the calibrated QPM. We will contrast the IRFs for a cost-push shock and an aggregate demand shock. We will also revisit the various transmission channels in the canonical QPM.

[VIDEO M3_8_IRFS FOR COST-PUSH SHOCK](#)

After studying the IRFs for a cost-push shock in great detail, the analysis of the demand shock will be straightforward. Thus, we will keep the discussion short and emphasize only the differences that allow us to distinguish cost-push and demand shocks.

The numbering of the IRFs follow a logical order in which we will discuss the various transmission mechanisms in the model:

Aggregate Demand Shock



1. A transitory demand shock, such as a one-time fiscal stimulus, affects output directly through the IS curve. As the IRF shows, the output gap increases immediately, and it remains positive for several quarters due to the persistence of the business cycle.

2. The above-normal demand increases input costs for domestic producers because of wage pressures due to overtime and faster depreciation of capital due to higher capacity utilization. The resulting pressure on inflation is captured by the real marginal cost term in the Phillips curve which includes the output gap. As the IRF shows, inflation increases above target.

3. The central bank observes an overheated economy with booming output and rising inflation. Monetary policy responds by gradually raising the interest rate according to the policy reaction function. Notice that there is no trade-off between the central bank's two objectives. Both inflation and output are high, prompting a hike in the policy rate.

4. The higher interest rate on domestic assets induces capital inflows and triggers an immediate appreciation of the nominal exchange rate in line with the UIP condition.
5. Monetary conditions become unambiguously tighter. Since the policy interest rate increases more than inflation, the real interest rate gap becomes positive. The real exchange rate gap turns negative on the back of nominal appreciation and high domestic inflation.
6. Tight monetary conditions dampen aggregate demand. The high real interest rate encourages saving instead of consumption and investment, while the strong real exchange rate reduces exports and favors imports. Over time these forces cool down the economy and bring output back to its long run trend.
7. The strong real exchange rate and closing domestic output gap also curb inflationary pressures in the economy.
8. As inflation returns to target and the positive output gap disappears, the central bank lowers the policy rate back to its neutral level.

There is one key difference between a cost-push shock and a demand shock that should hold in any reasonable calibration. After a cost-push shock, inflation and output move in opposite directions. This reflects a difficult trade-off that monetary policy is facing. For example, after an inflationary cost-push shock, the central bank must tighten monetary conditions and sacrifice some output to bring inflation back to target. In contrast, a demand shock moves inflation and output in the same direction. This presents a much more favorable situation for the central bank, as it can achieve both goals with the same policy action. For example, after an expansionary demand shock, tightening monetary conditions will both reduce inflation and bring economic activity back to its long-term trend. This property of the model is often referred to as "divine coincidence" in the literature.

Effect of Parameter Changes on the IRFs

In this unit, you will learn how to compare the IRFs for different calibrations of the QPM. Conveniently, IRIS allows us to calculate and plot automatically the model responses under different parameterizations. Through studying the effects of parameter changes on the IRFs, we can better understand how structural factors – for example, the credibility of the central bank – affect the transmission channels in the model.

In the following videos, we will adjust the share of backward-looking firms in the Phillips curve, and analyze the resulting change in the model's IRFs.

[VIDEO M3_9_CHANGING INFLATION PERSISTENCE IN THE PHILIPS CURVE I](#)

[VIDEO M3_10_CHANGING INFLATION PERSISTENCE IN THE PHILIPS CURVE II](#)

Exercise: Effect of changing the monetary policy reaction function

This exercise will walk you through the following scenario:

The new head of the central bank declares that he is much less worried about inflation volatility, but he cares deeply about output fluctuations and unemployment. He also convinces the monetary policy committee that

they should use the policy rate much more actively to manage economic activity in the country. In short, he wants to change interest rates faster and more aggressively in response to demand conditions. He asks his staff to recalibrate the bank's QPM to reflect this policy change.

[VIDEO M3_11_CONCLUDING MODULE 3](#)

QPM modeling - Modul 4

VIDEO M4_1_ABOUT MODUL 4

Preparing a Simple Data File: General Structure of the Data File

The **data file** is a simple CSV (Comma-Separated Values) text file in which we store time series data in a predefined structure.

Structure of the data file

- Time series entries are organized in columns
- The entries (columns) are separated by commas (,)
- First column contains dates
- First row contains names of the time series entries
- Second row contains descriptions (or comments) of the entries. It is important that the descriptions contain complete information about each series including variable name, source, and units. The second row must have the keyword "Comment" in the first column.

The date format convention

- Dates in the first column are by default in format YYYYFP, where:

YYYY is a four-digit year number

F defines the frequency of the time series (M=monthly, Q=quarterly, H=biannual, Y=annual)

P defines the period of the entry for the specified year and frequency

Examples:

- 1) February 2019 is translated to 2019M2
- 2) Second quarter of 2019 is written as 2019Q2
- 3) First half of 2019 is written as 2019H1
- 4) Year 2019 is written as 2019Y1

Preparing a Simple Data File: Useful Tips

Here are a few tips to better work with the data file:

- 1) Avoid using spaces and special characters (such as +-*/@#\$\$%^&) in the names of the entries in the first row:
 1. Incorrect: gdp nom (USD)
 2. Correct: gdp_nom_USD
- 2) Avoid starting the entry names with a number or a special character:

3. Incorrect: 14d_interest_rate
4. Correct: interest_rate_14d
- 3) Use period (".") as a decimal point delimiter when writing the entry values.
 5. Incorrect: 5,4
 6. Correct: 5.4
- 4) Avoid using a thousands delimiter when writing entry values because commas (",") get confused with column separators in CSV files.
 7. Incorrect: 10,000.00
 8. Correct: 10000.00
- 5) Leave a blank space for the missing observations. Avoid using "NA", "NAN" or any other acronym to represent a missing observation.

VIDEO M4_2_LOADING AND SAVING A DATABASE

`d = dbload('filename.csv');`

`dbsave(database_name,'filename.csv');` for example `dbsave(d,'saved_db.csv');`

VIDEO M4_3_HOW TO WORK WITH DATABASE IN MATLAB

How to create an empty database?

`db = struct();`

How to add a new entry into the existing database?

`database_name.entry_name = [values for the new entry];` for example `d.LGDP = 100*log(d.GDP);`

How to remove existing entry from the database

`database_name = rmfield(database_name,'series_name');` for example `d = rmfield(d,'S');`

VIDEO M4_4_TIME SERIES IN MATLAB

How to create a new time series?

`ts = tseries([data range],[vector/matrix of values]);` for example:

`ts1 = tseries(mm(2018,1):mm(2018,6), [1 2 3 4 5 6]);`

`ts2 = tseries(qq(2018,1):qq(2018,3), [1 2 3]);`

How to set a value for a specific date?

`ts([vector of dates]) = [vector/matrix of values];` for example `ts1(mm(2018,3)) = 10;`

How to retrieve values from time series?

- 6) Store them in time series

- vals = name of tseries{vector of dates}; for example vals = ts1{mm(2018,2):mm(2018,3)};
- 7) Store them in vector/matrix
- vals = name of tseries{vector of dates}; for example vals = ts1(mm(2018,2):mm(2018,3));

How to retrieve information about the time series variable?

get(tseries,property as string); for example get(ts1, 'range');

How to stack time series horizontally?

[timeseries1 timeseries2]; for example [ts1 ts2];

How to stack time series vertically/overlapping?

Stacking time series vertically/overlapping with data points in time series on the right taking precedence over data points in time series on the left.

[timeseries1; timeseries2]; for example [ts1; ts2];

Data Transformation Commands in MATLAB: Seasonal Adjustment

In macroeconomics, we often work with data that are subject to seasonal (i.e. periodic) oscillations associated with specific periods of a year. For example, agricultural output is high during the main harvest season and low in the other periods of the year. Because seasonal movements in the data reflect specific repeating patterns during the year rather than changes in a business cycle or economic fundamentals, we almost always work with seasonally adjusted data (i.e. data after removing effects of seasonal factors). We do not seasonally adjust annual data because they cannot exhibit intra-year seasonality by definition.

The IRIS toolbox has a third-party seasonal adjustment program called X13-ARIMA-SEATS, which is developed and maintained by the U.S. Census Bureau. The function performing the seasonal adjustment in IRIS is called x12()

seasonally_adjusted_tseries = x12(original_tseries); CPI_SA = x12(d.CPI_U);

VIDEO M4_5_CONVERTING TIME SERIES TO DIFFERENT FREQUENCIES

Converting time series into lower frequency the option *method* can be:

'mean' = mean of the values from all periods of the original time series which fall into the respective lower frequency period

'first' = value from the first period of the original time series which falls into the respective lower frequency period

'last' = value from the last period of the original time series which falls into the respective lower frequency period

CPI_U_y = convert(d.CPI_U,'y',Inf,'method',@mean)

Converting time series into lower frequency the option *method* can be:

'cubic' = cubic interpolation with low frequency value in the middle of the higher frequency grid

'quadsum' = quadratic interpolation such that sum of the interpolated values matches value of the original series in the respective lower frequency period

'quadavg' = quadratic interpolation such that average of the interpolated values matches value of the original series in the respective lower frequency period

```
CPI_U_yq = convert(d.CPI_U_y,'q',Inf,'method','quadavg')
```

Data Transformation Commands in MATLAB: Computing the Growth Rate

VIDEO M4_6_COMPUTING THE GROWTH RATE

To compute growth rates over more than one period using `pct()` function, we have to specify second argument for the length of the window
`pct(ts,12)` for 12-months growth rate if `ts` is in monthly frequency

In the model context, we will often work with log-approximation of the growth rates which is based on the approximation formula (first order Taylor expansion)
$$\log(1+x) \approx x \quad \text{for } x \text{ close to } 0$$

```
d.GDP_GROWTH_FORMULA = 100*(d.GDP/d.GDP{-1}-1);
```

```
d.GDP_GROWTH_FUNCTION = pct(d.GDP);
```

```
d.GDP_GROWTH_LOGAPPROX = diff(d.LGDP);
```

Data Transformation Commands in MATLAB: The DBBATCH Function

The `dbbatch` function is used to apply the same transformation to all or a subset of database entries. We can use `dbbatch()` function if we want to apply the same transformation (i.e seasonal adjustment, computing growth rates) to all or a specific subset of database entries,

```
new_database = dbbatch(original_database, name pattern for processed entries, transformation command);
```

VIDEO M4_7_USING DBBATCH

This function is useful if you want to apply the same transformation to all database entries or to a subset of database entries.

Compute growth rates of all database entries and storing them in the new database

new_database = dbbatch(original_database, name pattern for processed entries, transformation command);

```
db_new = dbbatch(d, '$0_growth', 'pct(d.$0)');
```

\$0 is replacing the original name of the variable (build-in function in MATLAB).

Computing growth rates only for a selected database entries by listing the entries - option **namelist**

```
db_new = dbbatch(d, '$0_growth', 'pct(d.$0)', 'namelist', 'GDP_RW', 'CPI_RW', 'etc', 'etc', 'etc');
```

Computing growth rates only for a selected database entries by matching pattern of the entries - option **namefilter**

```
db_new = dbbatch(d, '$0_growth', 'pct(d.$0)', 'namefilter', '.*_RW');
```

.* is replacing any character in the timeseries and possibility of multiple characters.

Learning Activity 2

0 points possible (ungraded)

Using the same csv database data_M4_LA.csv, compute percentage change of all entries that end with _EU using the dbbatch function. Before you do that, make sure you first load the csv file into a new database called dt.

There is no need to click the submit button for this activity, but if you had any difficulty in performing the tasks, click on the Show Answer button below to see the proper commands.

Data Transformation Commands in MATLAB: The Hodrick-Prescott Filter

[VIDEO M4_8 HODRICK-PRESCOTT FILTER](#)

$$\min_{\tau_1, \dots, \tau_T} \left(\underbrace{\sum_{t=1}^T (y_t - \tau_t)^2}_{\text{distance of trend from data}} + \lambda \underbrace{\sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2}_{\text{smoothness of the trend}} \right)$$

The Parameter λ determines the trade-off between the two objectives:
 $\lambda = 0$... trend coincides with the actual data $\lambda \rightarrow \infty$...linear trend

HP filter in Iris is implemented by this function:

`[trend, gap]=hpf(name_of_tseries, 'lambda', lambda value)`

Because the HP filter assumes that the time series is stationary in differences, we typically apply HP filter on the logarithm of the time series

HP filter decomposes time series into a component consisting of lower frequency movement (trend) and higher frequency movement (cycle, gap). The amount of volatility allowed to be associated with a trend is determined by a parameter LAMBDA (λ). The higher the value of lambda is, the less volatile is the trend. The lower the value of lambda is, the bigger part of volatility is explained by the trend. Default value of lambda for quarterly data is 1600, if you do not specify otherwise.

The HP filter assumes that the time series grows linearly. However, we often deal with time series that grow exponentially (GDP, CPI, credit, etc.). Therefore, we need to make logarithm of the series before doing HP filter.

```
[LGDP_tnd, LGDP_gap] = hpf(d.LGDP);
```

```
[LGDP_tnd, LGDP_gap] = hpf(d.LGDP, 'lambda', 100);
```

How to specify the range of the dates that we want to include in the filter?

```
[LGDP_tnd, LGDP_gap] = hpf(d.LGDP, qq(1996.1):qq(2008,3));
```

How to impose the judgement of the level of the trend?

```
[LGDP_tnd, LGDP_gap] = hpf(d.LGDP, qq(1996.1):qq(2008,3), 'level', 'd.LGDP{qq(2008,3)-4}');
```

This means that the trend would be in this period lower than LGDP by 4.

Data Transformation Commands in MATLAB: The Band-Pass Filter

[VIDEO M4_9 BAND-PASS FILTER](#)

In this unit, you will learn how to use Band-Pass (BP) filter, which is another type of univariate filter. The BP filter allows us to decompose the time series into different components based on their different frequency ranges.

For example, we can decompose the output into:

Trend = components with periodicities longer than business cycle

Gap = components with business cycle periodicities

Noise = components with shorter periodicities than business cycle (i.e. noise in data, discretionary movements in output etc.).

BP filter in Iris is implemented by this function: `bpass`

```
bp_result = bpass(name_of_tseries, band of periodicities);
```

```
LGDP_tnd_bp = bpass(d.LGDP,[32 Inf]);
```

```
LGDP_gap_bp = bpass(d.LGDP,[6 32]);
```

```
LGDP_noise_bp = bpass(d.LGDP, [2 6]);
```

Output Reports and Data Visualization: Creating PDF Reports with IRIS

To start creating a report, we use the Iris function `Report.new()`:

```
Report_variable = Report.new(title of the report, orientation of the report)
```

Example of creating new report with landscape orientation:

```
Rep = Report.new('My first report','orientation','landscape')
```

Once we build the content of the report (which we will explain later), we can generate the pdf file by using function `publish()`:

```
publish(Rep,'my_first_rep.pdf','maketitle',true)
```

Output Reports and Data Visualization: Adding a Figure to the Report

VIDEO M4_10 ADDING A FIGURE TO THE REPORT

To add a figure to an existing report object use a sequence of the commands: `figure`, `graph`, and `series`. Note that we have to call this functions as a function of the existing report object:

- Adding a new figure window into the report `rep.figure(figure title);`

- Adding a graph into an existing figure window in the report `rep.graph(graph title);`

```
rep = Report.new('Report with figures');
rep.figure('My first figure');
rep.graph('My first graph');
rep.series('GDP (100*log)', d.LGDP);
rep.series('GDP trend (100*log)', d.LGDP_tnd);
publish(rep,'report1.pdf');
```

To add more than one graph into an existing figure, we can use another sequence of a `graph()` command followed by `series()` commands:

```
rep = Report.new('Report with figures');
rep.figure('My first figure');
rep.graph('My first graph');
rep.series('GDP (100*log)', d.LGDP);
rep.series('GDP trend (100*log)', d.LGDP_tnd);
rep.graph('My second graph');
rep.series('GDP gap (percent)',LGDP_gap);
publish(rep,'report1.pdf');
```

Output Reports and Data Visualization: Adding a Figure to the Report

When creating the reports in IRIS, keep these tips in mind:

Legends:

- To display a legend in a graph use 'legend' option in `graph ()` command
- Legend entries are taken from the first arguments of the `series ()` commands
- To set default location of the legend in the graph use 'legendlocation' option

Example 1: `rep.graph ('My first graph','legend',true,'legendlocation','SE');`

```
rep.series ('GDP(100*log)',d.LGDP);
```

Ranges:

- To plot a time series on a defined range use option 'range' in `figure ()` or `graph ()` command

Example: `rep.graph ('My first graph', 'range',qq(2000,1):qq(2008,1));`

Date format:

- To set a specific format for dates use option 'dateformat' in figure() command

Example: rep.figure('My first figure', 'dateformat', 'YYFP');

Examples:

```
dt=dbload('data_M4_LA.csv');
dt.CPI_SA = x12(dt.CPI_U);
rep = Report.new('Seasonal Adjustment');
rep.figure('Seasonal Adjustment');
rep.graph('Seasonal Adjustment', 'legend', true, 'legendlocation', 'SE');
rep.series('CPI unadjusted',dt.CPI_U);
rep.series('CPI seasonally adjusted',dt.CPI_SA);
publish(rep,'LA3.pdf');
```

Implementing a02_makedata.m

[VIDEO M4_11 REVIEWING THE DATABASE FILE](#)

[VIDEO M4_12 DATABASE TRANSFORMATIONS](#)

Important commands:

dbbatch – when you want to apply any function to selected or all series, for example:

Seasonal adjustment for series with _U

```
d = dbbatch(d,'$1', 'x12(d.$0,Inf,"mode","m")', 'namefilter', '(x*)_U', 'fresh', false);
```

Log approximation of all entries except series in exceptions

```
d = dbbatch(d,'L_$0', '100*log(d.$0)', 'namelist', fieldnames(d)-exceptions', 'fresh', false);
```

Define the real exchange rate

```
d.L_Z = d.L_S + d.L_CPI_RW – d.L_CPI;
```

Growth rate qoq, yoy

```
d = dbbatch(d,'DLA_$1', '4*diff(d.$0)', 'namefilter', 'L_(.*)', 'fresh', false);
```

```
d = dbbatch(d,'D4L_$1', 'diff(d.$0,-4)', 'namefilter', 'L_(.*)', 'fresh', false);
```

[VIDEO M4_11 REPORTING PROCESSED DATA](#)

QPM modeling - Modul 5

VIDEO M5_1_ABOUT MODUL 5

Basics of Multivariate Filtration: Trends and Gaps

Our QPM works with trends and gaps. Any real variable can be decomposed into the **trend** and **gap** components.

Trends capture long-term changes and low frequency events. Trends are driven by structural changes and factors such as productivity. They generally lie outside the scope of monetary policy.

Gaps reflect business cycle dynamics, with frequencies usually ranging from 8 to 32 quarters. They are often measured as percentage deviation from the trend. Importantly, monetary policy **does** affect gaps, and that's what we are most interested in for our monetary policy analysis. The QPM is often referred to as a "Gap model".

Both trends and gaps are unobserved variables and must be estimated, therefore we need to use filters.

VIDEO M5_2_BASICS OF MULTIVARIATE FILTRATION

It takes into consideration gaps and trends from other variables that might have effect on our particular variable of interest.

It avoids the risk of end-point bias as univariate filtration techniques (HP, BP) are basically weighted moving average of past, current and future values.

The Kalman filter is a useful and popular tool that allows us to implement the multivariate filtration approach. Applying multivariate filtration means using information from multiple variables to filter the variables of interest. Recall that in our last example, we looked at the actual output dynamics to estimate unobserved gap. However, we also wanted to use information about low inflation to try to obtain "better" estimates of unobserved variables.

By using this additional information, we expect to obtain "better" estimates of unobserved variables. Also, such a filter would be more robust to end-point bias and other structural problems of univariate filters.

The Kalman filter has desirable statistical properties. It provides optimal linear estimation of unobserved variables based on the past information, in the sense of minimizing mean squared error. In the case of normally distributed errors, it is optimal among not only linear, but all the classes of estimators.

To make the idea of multivariate filtration operational, we need to provide the filter with information on how different variables are related to each other. In other words, together with the observations database, we need to provide two other inputs: (i) a structural model linking the variables and (ii) the values of the model parameters.

In the next two videos, we discuss (1) key steps of the Kalman filter algorithm and (2) how to deal with the first input – structural model. We will discuss the second input – values of the model parameters – in the

following section. If you want to learn more about the Kalman filter, consider the optional section “The Kalman filter algorithm”.

The Kalman filter and state-space models

The Kalman filter requires a structural model linking the variables together, represented in the state-space form. This leads to two questions: Where do we take the structural model from? And what is the state-space form?

The structural model can be motivated by economic theory. For example, we can use our structural QPM. It is a model linking all our variables. Coming back to our simple example of output gap filtration, Phillips curve would inform the filter about the relationship between the output gap and inflation.

A model in the state-space form consists of 2 types of equations.

- Measurement, or observation, equations describe the static relationship between the observable and the unobservable, state, variables. For example, actual GDP can be decomposed into 2 unobserved components – gap and trend.
- Transition, or state, equations describe the dynamics of the unobservable, state, variables. For example, output gap may exhibit inertia. Or it may also depend on the real interest rate gap, as in the IS curve.

State-space models

- 1. Measurement (observation, signal) equations →**
relationship between *observed* and *state/unobserved* variables
– Example: Output gap ↔ Real GDP
- 2. Transition (state) equations →**
dynamics of the *state/unobserved* variables
– Example: Output gap ↔ output gap with lag
– Example: Output gap ↔ real interest rate gap

[VIDEO M5_3_THE STATE-SPACE MODEL AND THE QPM](#)

In particular, we need to deal with the dynamic equations of the QPM, but the state-space model allows for dynamics only in transition equations for unobservable variables.

[VIDEO M5_4_KEY STEPS OF THE KALMAN FILTER ALGORITHM](#)

Intuition of Kalman Filter Application: Simple model with one variable

Outcomes of multivariate Kalman filtration depend on the inputs that we provide to the filter. Besides the database of observed variables, we need to provide a structural model linking the variables and values of the model parameters. In the previous section, we concluded that we can use our QPM as the structural model, providing reasonable stylized representation of the economy. In this section, we are going to focus on the QPM parameters, which include coefficients, steady states, and standard deviations of shocks. In particular, we are going to build intuition of how changes in these inputs can affect filtration outputs.

The videos in this unit show a simple example of the Kalman filter's application to one variable – GDP – to filter its unobserved components. In the next unit, we will show an example of the Kalman filter's application to a model with two variables – GDP and inflation.

Files that show examples of Kalman filter application introduced in this section can be found here. Please note that before running any .m file you first need to start an IRIS session by running the m file called start.m.

*Note that this will be a shared folder with a blue icon. You will not be able to edit this shared folder. However, given that you will be asked to make changes to the codes as you are progressing with the material and completing course assignments, you should create a copy of the codes which you can later edit. To do that, right click on the folder “model_aux_m5” and select “Copy”. Then, right click in the Current Folder Panel and select “Paste.” Make sure to provide a name to the folder that is different from the original folder name “model_aux_m5”.

VIDEO M5_5_ SIMPLE MODEL WITH ONE OBSERVABLE VARIABLE

First, we need to formulate a model linking the three variables together. In particular, actual GDP can be decomposed into gap and trend. The cyclical component, output gap, follows the autoregressive process of order one with 0 mean. That implies that any output gap gradually closes in the medium term. The trend follows random walk with drift where the drift parameter, C2, reflects the steady state growth of the economy.

• Output = gap + trend

$$y_t = \hat{y}_t + \bar{y}_t$$

$$\hat{y}_t = c_1 \hat{y}_{t-1} + \mu_t \quad \mu_t \sim N(0, \sigma_\mu^2)$$

$$\Delta \bar{y}_t = c_2 / 4 + \eta_t \Rightarrow \eta_t \sim N(0, \sigma_\eta^2), E(\mu_t \eta_t') = 0$$

Now, we need to set values for the parameters. We have 5 parameters there: b1, ss_DLA_GDP_BAR, rho_DLA_GDP_BAR, SHK_L_GDP_GAP, SHK_DLA_GDP_BAR. Getting numbers for the parameters are mostly coming from their estimation using Maximum Likelihood estimation, Bayesian approach (b1, rho_, SHK) or we can calibrate our parameters based on some judgement (economic intuition, research papers,

etc.). For example, estimation the steady state of the variable is set to the long-term average of growth (long-term growth of GDP).

For shocks, the exact size is not so much important as the relative size, as the filter will rescale them. For example, the output gap SHK has bigger size than the output trend SHK, because we allow the output gap to be more volatile than the actual output trend.

```
10
11 |transition_shocks
12 'Shock: Output gap (demand)'   SHK_L_GDP_GAP
13 'Shock: Potential GDP growth'  SHK_DLA_GDP_BAR
14
15 |parameters
16 b1, ss_DLA_GDP_BAR, rho_DLA_GDP_BAR
17
18 |transition_equations
19 % Output decomposition into gap and trend
20 L_GDP = L_GDP_GAP + L_GDP_BAR;
21
22 % Output gap dynamics
23 L_GDP_GAP = b1*L_GDP_GAP(-1) + SHK_L_GDP_GAP;
24
25 % Output trend dynamics (define trend growth, specify dynamics for the growth)
26 DLA_GDP_BAR = 4*(L_GDP_BAR - L_GDP_BAR(-1));
27 DLA_GDP_BAR = rho_DLA_GDP_BAR*DLA_GDP_BAR(-1) + (1-rho_DLA_GDP_BAR)*ss_DLA_GDP_BAR + SHK_DLA_GDP_BAR;
28
```

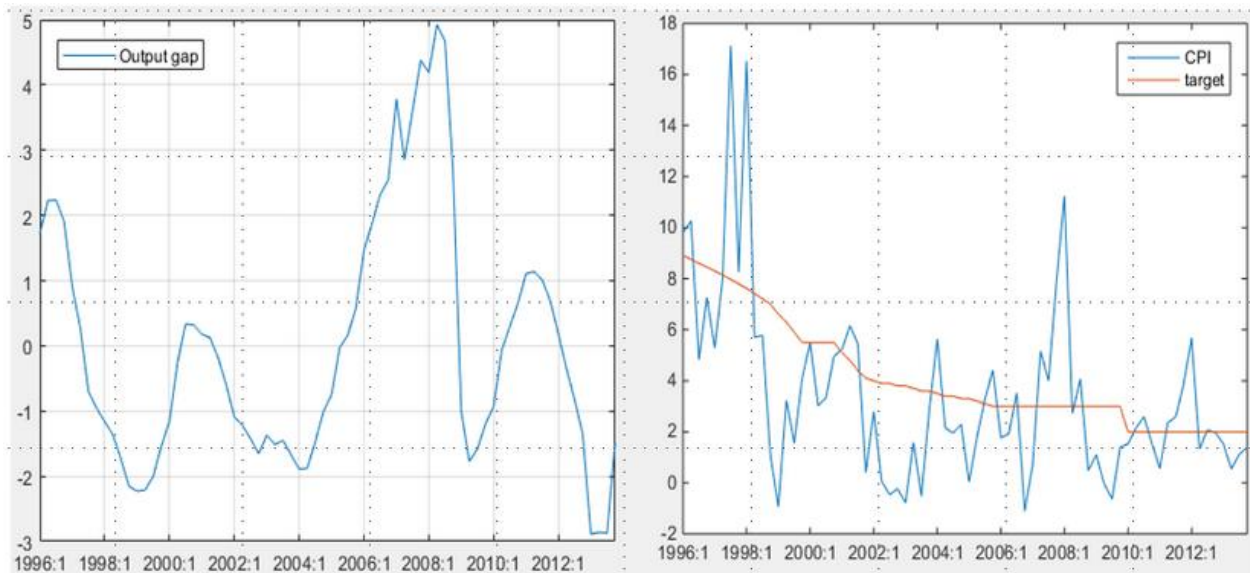
[VIDEO M5_6_CALIBRATION OF THE SIMPLE MODEL WITH ONE OBSERVABLE VARIABLE](#)

[VIDEO M5_7_KALMAN FILTRATION USING THE SIMPLE MODEL WITH ONE OBSERVABLE VARIABLE](#)

Intuition of Kalman Filter Application: Simple model with two variables

Recall the results of Kalman filtration for our one-variable model (left graph). The output gap declines abruptly in 2008, reaching -1.8% in 2009. However, the negative output gap in 2009 is much smaller than in 2013, when it reaches -2.9% before rolling back to -1.5% in 2013Q4.

Observe, however, that decline of inflation at the outset of the global financial crisis in 2008-2009 was much larger than in 2013 (right graph). Inflation can be used as an additional source of information about the output gap, because inflation is related to the output gap through the Phillips curve. For example, low inflation in 2009 may indicate that negative output gap was very large at that time, while inflation dynamics closer to the target during 2013 suggest milder disinflationary pressures.



VIDEO M5_8_SIMPLE MODEL FOR GDP AND INFLATION, PART 1


VIDEO M5_9_SIMPLE MODEL FOR GDP AND INFLATION, PART 2

VIDEO M5_10_KALMAN FILTRATION USING SIMPLE MODEL FOR GDP AND INFLATION

The most important information here is that the standard deviations for gaps should be higher than for trends and standard deviations for more volatile variables should be higher than for less volatile variables. It means that shocks for core inflation should be lower than for headline, or for real variables lower than for financial variables.

Learning Activity 7

0 points possible (ungraded)

 [Keyboard Help](#)

How would you usually calibrate the standard deviations of shocks in a small structural model for an economy with a floating exchange rate?

>
=

std_SHK_DLA_Z_BAR
<
std_SHK_L_S

Implementation of Kalman Filtration in MATLAB: The Structure of a03_kalmanfilter.m

In the previous section, we considered examples of Kalman filter application. In particular, we discussed how the output gap and the output trend can be filtered using simple models. In this section, we will learn how to apply the Kalman filter to the whole dataset used by the QPM. That is, we will filter all the unobservable variables – trends and gaps for various variables – simultaneously!

Recall that we need to provide a model to the Kalman filter that would interrelate all the variables in some economically meaningful way. That is exactly what the QPM does! So, we can use this model as the underlying economic structure to jointly estimate all trends, gaps, and structural shocks. In the next video, we discuss the steps that we need to take to run the Kalman filter in Matlab and IRIS.

[VIDEO M5_11_STRUCTURE OF A03_KALMANFILTER.M](#)

[VIDEO M5_12_OBSERVATIONS OF DOMESTIC AND FOREIGN VARIABLES](#)

The Kalman filter can be called in Matlab using IRIS function filter().

```
[m_kf,g,v,delta,pe] = filter(m,dd,sdate:edate);
```

There are several inputs to provide to the function filter():

m - model object in state-space form (solved for rational expectations);

dd – database with observations for measurement variables;

sdate:edate – data range to run the Kalman filter.

The function filter() has several outputs, including:

m_kf – model object with updates of standard deviations;

v – variance scale factor;

Clarification: to run the Kalman filter, we had to define standard deviations for all the shocks. We may have some priors about how sizes of different shocks are relative to each other, but usually we know much less about the absolute size of the shocks. For example, we may assume that aggregate demand shocks in our economy are larger than cost-push shocks, but may not know the exact number for the standard deviation of demand shocks. Then, we can use option "relative" of the filter() function (described below). In model calibration, we can focus on the relative size of standard deviations of shocks (as we did in the previous section) and allow the filter() function to re-calculate their absolute size by multiplying by some scalar. The filter() function will (i) estimate the variance scale factor, v, and (ii) rescale all the shocks in the model m_kf, multiplying their variances by the scale factor.

g – structure with filtered/smoothed data.

In particular, point estimates of the state variables are provided in g.mean.

In the a03_kalmanfilter.m file, point estimates of all the unobservable variables – gaps and trends – are saved in g.mean. We add these estimates to the database d and save it to the file kalm_his.csv:

```
h = g.mean;
```

```
d = dbextend(d,h);
```

```
dbsave(d,'results/kalm_his.csv');
```

Function `filter()` has a number of options. Here are some of them:

'output=' determines the type of estimates to be saved by the filter in the structure `g` (recall the Basics of Kalman Filter unit – there are 3 types of outputs that can be used):

'predict' – one-step ahead predictions from the 1st step of the Kalman filter;

'filter' – filtered estimates from the 2nd step of the Kalman filter;

'smooth' (by default) – smoothed estimates from the Kalman smoother. That's the option we normally use.

'relative=' determines whether calibration of standard deviations of shocks will be treated as relative or absolute:

'true' (by default) – calibration will be treated as relative. Standard deviations of shocks will be rescaled by the factor v and the model with re-scaled shocks will be saved in `m_kf` (see discussion above). That's the option we often use;

'false' – calibration will be treated as absolute and standard deviations of shocks will not be re-scaled.

'initCond=' determines how the starting values to initialize the Kalman filter will be provided (recall the Basics of the Kalman Filter unit – to start iterations, the Kalman filter requires starting value for the state variables and their prediction error variance):

'stochastic' (by default) – the Kalman filter will calculate model-implied asymptotic distribution for these values, that is, steady state values for the states;

'fixed' – starting values for the states will remain at the steady state, but initial prediction error uncertainty will be restricted to zero. Thus, in contrast to the default 'stochastic' option, filter will fix starting values of the states;

'optimal' – the filter start from the fixed numbers that are estimated optimally (likelihood maximizing);

`struct` – you can specify starting values of your own by providing the structure `struct`.

In the `a03_kalmanfilter.m` file, we used default options:

obtained Kalman smoother estimates of the unobservable variables;

treated calibration of standard deviations of shocks as relative, allowed the filter to re-scale them by the factor v ;

used steady-state values and their prediction error variance of state variables as starting values for the Kalman filter iteration.

You can learn more about the `filter()` function from the IRIS manual.

Implementation of Kalman Filtration in MATLAB: Creation of Reports with the Filtration Results

[VIDEO M5_13_ CREATING A REPORT WITH FILTRATION RESULTS](#)

[VIDEO M5_14_ DECOMPOSITION INTO FACTORS](#)

Interpretation of the Initial Macroeconomic Conditions

So far you've learned how to estimate all the unobserved variables and shocks. Now it is time to recall why we need the QPM. Our goal is to use the QPM to produce forecasting and policy analysis, because monetary policy should be forward-looking and inflation forecast is necessary to formulate such policy.

Initial Conditions

- **Inflation forecast** is necessary to formulate forward-looking monetary policy
- **Assessment of the current (most recent) state of the economy** is one of the key inputs, serves as the *initial conditions for the forecast*
 - implications for future development of the economy
- **Initial conditions:**
 - An assessment of actual inflationary pressures, business cycle position, monetary conditions, ...
 - Unobserved variables inferred from data
 - External environment is part of the story

One of the key inputs to the forecast of future developments in the economy is an assessment of the current (or most recent) state of the economy, which serves as the initial conditions for the forecast. In other words, the current state of the economy has implications for the future development.

For example: assume that you know the current state of the business cycle reflects an opening positive output gap. With this information, you can probably assume something about the inflation going forward. If you also have information on the current exchange rate misalignment, you might be able to say even more about the future inflation.

Initial macroeconomic conditions may include an assessment of actual inflationary pressures, business cycle position, monetary condition index and other elements of the overall state of the economy. Note that many of these elements are unobserved variables, which we have estimated using the Kalman filter (except for foreign output gap). For a small open economy, its external environment is also an important part of the story.

[VIDEO M5_15_ INTERPRETATION OF THE INITIAL MACROECONOMIC CONDITIONS](#)

QPM modeling - Modul 6

VIDEO M6_1_ABOUT MODUL 6

Calibration Tools and Strategy: How is the Calibration Cycle Defined?

We can outline the model calibration process with three tasks:



After the model is developed and calibrated, calibration of the model should be periodically reviewed based on:

- Identified issues while using the model
- Analysis of forecast errors

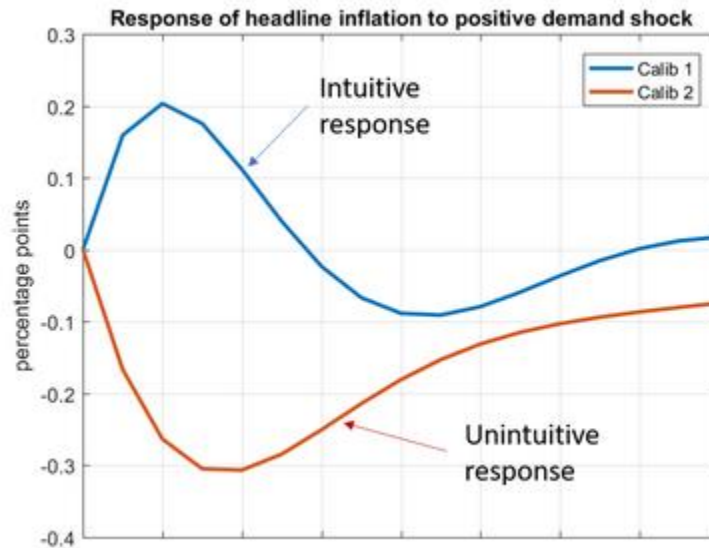
Now, let's look at the tools we can use to assess the performance of the model.

Calibration Tools and Strategy: Diagnostic Tools to Assess Model Performance

There are three tools to assess model performance:

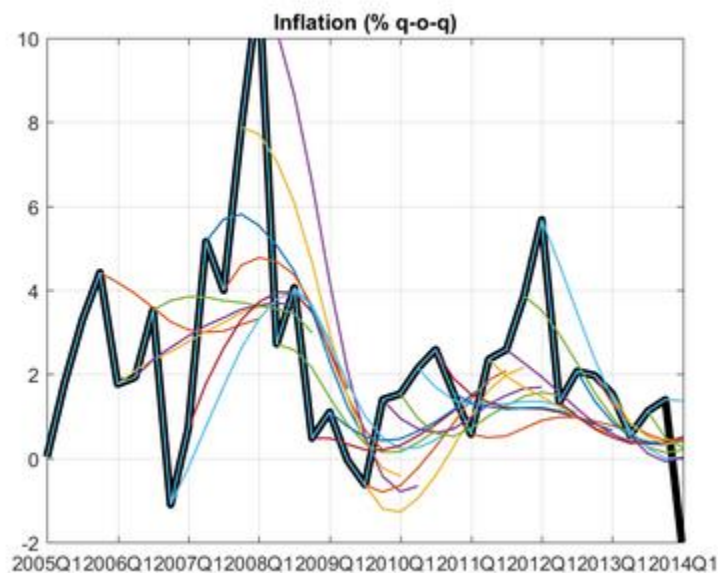
1. Impulse response functions:

- Impulse response functions (IRFs) are one of the three main diagnostic tools to assess calibration of the model. As you have seen in Module 3, IRFs are useful to assess' dynamic behavior of the model for a particular calibration.
- When assessing IRFs, we mainly check that:
 - Responses of model variables to various shocks have correct signs (variables move in expected directions)
 - Responses of variables to transitory shocks don't take too long to converge back to steady-states
 - Responses of variables to shocks are not oscillating (i.e. looking as waves)



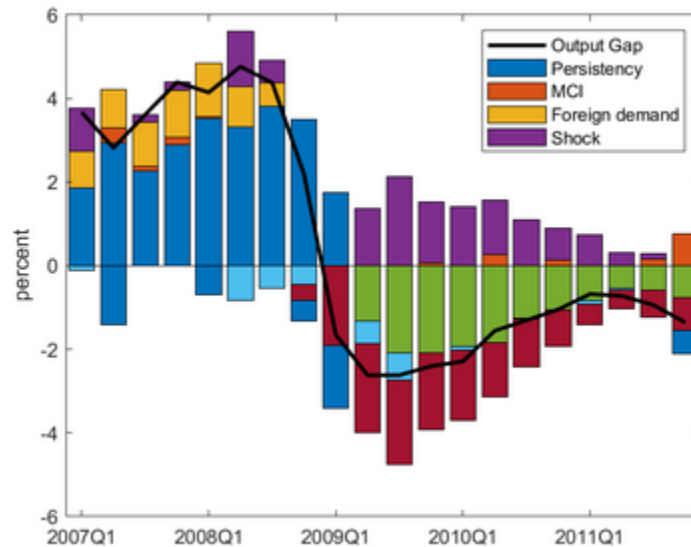
2. In-sample forecast performance:

- In-sample forecasts are another diagnostic tool. They are used to assess how well the calibrated model, if used in the past, would have predicted the data.
- In-sample forecasts show how the model forecasts would have look if we had run the model in all periods of relevant history. Broadly speaking, we would like the in-sample forecasts to closely follow the actual outturns.
- However, it is common to see instances where in-sample forecasts do not predict the out-turns very accurately. For example, it is reasonable to expect that in-sample forecasts would fail to predict increases in inflation induced by weather-related food supply shocks, since the model, by design, does not have the ability to predict weather.



3. Kalman filter decompositions of equations:

- Kalman filter decompositions of equations are another important diagnostic tool. Detailed explanation of the decompositions was given in Module 5.
- The decompositions help us to assess the ability of the model to interpret past economic developments through economist lenses. For example, a recession that caused weakening of foreign economies and subsequently depressed domestic demand. We should also try to interpret the unexplained factors captured by the shock components, referring to developments outside the model. Can the mitigating shock be explained by factors outside of the model (for example fiscal stimulus)?



Preparing the Initial Calibration: Calibration of Steady State Parameters

There are four specific steps to define the initial calibration in the model:

1. Calibration of steady state parameters
2. Calibration of trend dynamics
3. Calibration of core equations' coefficients
4. Calibration of shocks' standard deviations

In the next few units, we will review each step.

Notion of Steady State

Steady state levels of variables are values to which we expect the variables to converge after dissipation of business cycle fluctuations and of effects of shocks affecting long-run trend dynamics of these variables.

The convergence to steady state is expected to be over a 3-5 year horizon in case of business cycle fluctuations, but it could possibly be longer for shocks to long-run trends.

Steady state of the model and steady state parameters

Steady state of a variable is a value to which the variable converges over time.

Steady state of the model refers to the collection of steady states of all model variables.

Steady state parameter is a model parameter which, given the structure of the model, happens to coincide with the steady-state of some model variables.

It is obvious from the structure of the equation for potential growth that steady state of the potential growth $\Delta\bar{y}$ coincides with the parameter $\Delta\bar{y}^{ss}$:

$$\Delta\bar{y}_t = h_y\Delta\bar{y}_{t-1} + (1 - h_y)\Delta\bar{y}^{ss} + \varepsilon_t^{\bar{y}}$$

Steady state parameter

In steady state:

$$\begin{aligned}\Delta\bar{y} &= h_y\Delta\bar{y} + (1 - h_y)\Delta\bar{y}^{ss} \\ (1 - h_y)\Delta\bar{y} &= (1 - h_y)\Delta\bar{y}^{ss} \\ \Delta\bar{y} &= \Delta\bar{y}^{ss}\end{aligned}$$

The calibrated values are often informed by:

- Historical averages
- Announced long-term policy targets
- Economic intuition and results of economic research

| Model Variable | Steady State Parameter | Notes on calibration |
|--|------------------------|--|
| Domestic inflation target | $\bar{\pi}^{SS}$ | Based on announced or internal/informal inflation objective (in peg or crawling pegs we calibrate steady state of exchange rate depreciation instead of the inflation target) |
| Domestic potential output growth | $\Delta\bar{y}^{SS}$ | Typically average over a relevant recent history For advanced countries often around 2, for emerging and developing countries would be typically higher, e.g. between 2 and 5 |
| Real exchange rate depreciation/appreciation | $\Delta\bar{z}^{SS}$ | Look at averages over some relevant period. It is typically 0 for advanced economies vs. other advanced economies. For emerging and developing countries vs. advanced economies, it is typically negative (i.e. appreciation in the steady state) due to productivity and price convergence |
| Real interest rate | \bar{r}^{SS} | For advanced countries the value would be somewhere between 0.5 and 2. For emerging and developing countries can be higher due to higher required returns on capital. Remember: UIP in steady state $\bar{r}^{SS} = \bar{r}^{*SS} + \Delta\bar{z}^{SS} + prem^{SS}$ For developing countries, the \bar{r}^{SS} should imply positive premium $prem^{SS}$ typically between 1 and 4 pp p.a. |

The version of the QPM codes for Module 6 can be found here- note that this is the same set of codes that was provided to you in the very beginning of the course (in Course Software Guide). Please note that before running any .m file you first need to start an IRIS session by running the .m file called start.m.

VIDEO M6_2_EXAMPLE OF INITIAL CALIBRATION OF STEADY STATE PARAMETERS

Preparing the Initial Calibration: Calibration of Trends Dynamics

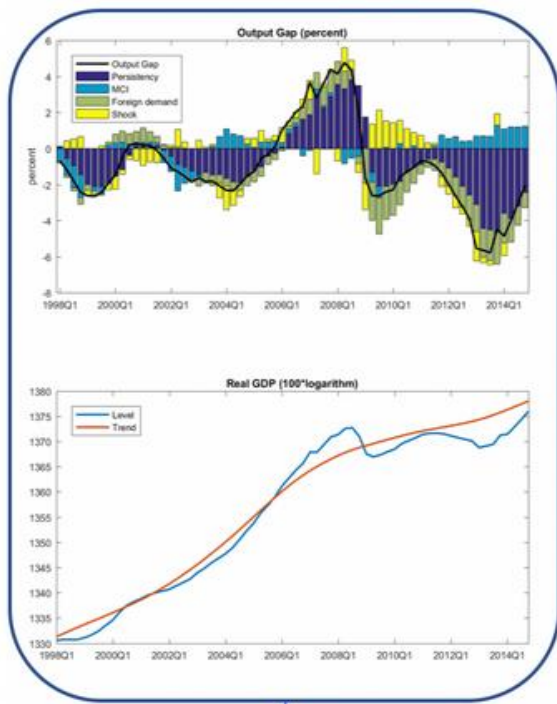
Calibration of trend dynamics

Trends in the QPMs are mostly modeled as simple autoregressive processes. This means that there are (almost) no economic restrictions on behavior of trends. For this reason, Kalman filter estimates would tend to explain observed data by movements in trends rather than gaps if we don't calibrate trend dynamics properly.

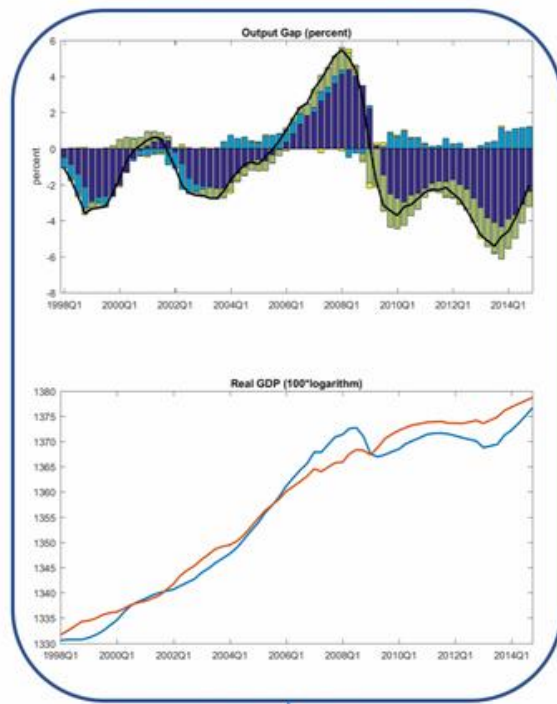
The only assumption about trends we make in the QPM is that they should be smooth. Let's consider a typical trend modeled as an autoregressive process of order 1 (e.g. potential growth):

$$\Delta\bar{y}_t = h_y \Delta\bar{y}_{t-1} + (1 - h_y) \Delta\bar{y}^{SS} + \varepsilon_t^{\bar{y}}$$

To make the trend smooth we set high persistency h_y and low standard deviation of the shock. This would mean that there won't be sharp changes in the trend; instead, small changes would be allowed to accumulate over time. Typical values for persistency are between **0.8** and **0.95**.



Desirable



Undesirable

Preparing the Initial Calibration: Calibration of Equations' Coefficients

Calibration of core equations' coefficients

Calibration of core equations' coefficients typically requires more iterations and experience. It is useful to start the calibration from good initial values, therefore it is worth to think about the initial calibration of these parameters in terms of how they reflect the characteristics of the modeled economy.

Calibrating interest rate rule (policy rule)

$$i_t = g_1 * i_{t-1} + (1 - g_1) * (i_t^{neutral} + g_2 * (E_t [\pi_{t+4}^4] - E_t [\pi_{t+4}^{TAR}]) + g_3 * \hat{y}_t) + \varepsilon_t^i$$
$$i_t^{neutral} = \bar{r}_t + E_t [\pi_{t+1}^4]$$

g_1 :in [0.4, 0.8] (must be in [0, 1)), larger value – bias towards “wait-and-see” policy

g_2 :in [0.5, 2] (must be positive), higher value – more hawkish policy

Note: $g_2 > 0$ satisfies Taylor principle

g_3 : calibrate relative to g_2 (must be non-negative)

$g_2 \geq g_3$: inflation stabilization is more important than output stabilization

Calibrating coefficients in uncovered interest rate parity (UIP) condition

$$s_t = (1 - e_1) * (E_t [s_{t+1}]) + e_1 * \left(s_{t-1} + \frac{2}{4} * (\pi_t^{TAR} - \bar{\pi}_t^* + \Delta \bar{z}_t) \right) + \frac{-i_t + i_t^* + prem_t}{4} + \varepsilon_t^s$$

e_1 : in (0.4, 0.9] (should be in [0, 1)), larger value – more backward-looking FX market and less volatile FX rate.

Preparing the Initial Calibration: Calibration of Standard Deviation of Shocks

We should calibrate standard deviations for all shocks in the model. If we don't calibrate standard deviation for some shock, the standard deviation will be set to 1 by default.

The larger the standard deviation of a shock (relative to other shocks) the stronger the tendency to explain the observed data with this shock.

As a general rule, the standard deviation of shocks in trends (e.g. potential output growth, equilibrium real interest rate) are smaller than corresponding shocks to levels (e.g. output gap shock or interest rate shock). As an initial calibration, you can set the standard deviation of the shocks in relation to volatility in the data. For example, standard deviations of shocks should be higher the larger is the volatility of the corresponding variable.

M6_3_EXAMPLE OF INITIAL CALIBRATION OF STANDARD DEVIATION OF SHOCKS

| Shock | |
|---|--|
| Output gap shock | ½ of standard deviation of quarterly (not annualized) GDP growth |
| Cost-push (inflation shock) | ½ of standard deviation of annualized quarterly inflation |
| Monetary policy (interest rate) shock | 1/3 of standard deviation of quarterly changes in interest rates (may be higher for policy frameworks not effectively controlling short-term interest rates) |
| UIP shock | ½ of standard deviation of quarterly FX depreciation (not annualized) |
| Potential output growth shock | ¼ of standard deviation of output gap shock |
| Equilibrium RER depreciation/appreciation shock | 1/5 of standard deviation of UIP shock |
| Neutral real interest rate shock | 1/3 of standard deviation of monetary policy shock |

Reviewing and Refining Initial Calibration: Finding a Unique Stable Solution

As the first thing after providing initial calibration or after modifying calibration in subsequent iterations, we have to make sure the model has a unique stable solution and that the steady state is consistent with our intuition.

Without going into details of how to solve rational expectations models, three outcomes are possible:

- 1) **Model has exactly one stable solution:** This means that from any state of the economy, there exists only one unique path to the long-term equilibrium. **We always want this to be the case.**
- 2) **Model does not have a stable solution:** This means that from any state of the economy, there is no path to the long-term equilibrium and the economy “explodes” instead.
- 3) **Model has more than one stable solution (indeterminacy):** This means that from the same state of the economy, there exists more than one path to the long-term equilibrium for the same policy rules.

The so-called Blanchard-Kahn conditions tell us how to determine which of these three cases applies based on the number of unstable eigenvalues and the number of control variables. Click [here](#) to learn more.

[M6_4_EXAMPLES OF SOLVING MODEL WITH RATIONAL EXPECTATIONS – PART I](#)

[M6_5_EXAMPLES OF SOLVING MODEL WITH RATIONAL EXPECTATIONS – PART II](#)

[M6_6_EXAMPLES OF SOLVING MODEL WITH RATIONAL EXPECTATIONS – PART III](#)

Reviewing and Refining Initial Calibration: Assessing Steady State Calibration

In refining the calibration of the model we should look for systematic over-/undershooting of forecasted variables. A common source of systematic over-/undershooting is improper calibration of steady state parameters.

To review the model's forecasting performance when we don't have any history of real-time forecasts, we use **in-sample forecast simulations** to show how well the model would predict future developments. 'In-sample' means that the initial state from which we start hypothetical forecasts has been estimated based on the whole data sample, and not just the truncated sample which ends right before the first forecast period. We often condition in-sample forecast simulations on external sector developments because the QPM is not supposed to forecast external sector. Conditioning on external sector developments tends to improve forecasting performance.

[M6_7_ASSESSING STEADY STATE CALIBRATION](#)

Reviewing and Refining Initial Calibration: Assessing Calibration of Trend Dynamics

The second step in assessing initial calibration is to look at the trends and see if they are not too volatile or misaligned with the actual data.

To inspect the trends, we compare the Kalman filter estimates of the trends with the actual data series. If we spot a problem, we usually adjust persistency or standard deviation of the shock in the corresponding trend equation.

In the video below, we explain this process with examples.

[M6_8_ASSESSING CALIBRATION OF TREND DYNAMICS](#)

Reviewing and Refining Initial Calibration: Assessing Calibration of Core Equations' Coefficients

The core equations' coefficients are very important for model dynamics and arguably the most difficult to calibrate.

In refining their calibration we inspect three diagnostic tools:

- 1- Impulse Response Functions (IRFs) – to compare the model dynamics with economic intuition and knowledge of the economy's behavior
- 2- Kalman filter results – to compare model-based interpretation of history with economists' views
- 3- In-sample forecasts – to assess model's forecasting performance

In the following videos, we will demonstrate how to detect common issues in calibration of the core equations' parameters.

[M6_9_USING IRF TO REFINE CALIBRATION OF EQUATION COEFFICIENTS](#)

[M6_10_USING KALMAN FILTER TO REFINE CALIBRATION OF EQUATION COEFFICIENTS](#)

[M6_11_USING IN-SAMPLE FORECASTS TO REFINE CALIBRATION OF EQUATION COEFFICIENTS](#)

Reviewing and Refining Initial Calibration: Assessing Calibration of Shocks' Standard Deviations

In this unit, we discuss how to assess the calibration of shocks' standard deviations, as well as how to detect and solve potential issues related to this group of model parameters.

[**M6_12_ASSESSING CALIBRATION OF SHOCKS' STANDARD DEVIATIONS**](#)

[**M6_13_SUMMARY**](#)

QPM modeling - Modul 7

VIDEO M7_1_ABOUT MODUL 7

Basics of Model Based Forecasting

A forecast is a key input for monetary policy decision making. Monetary policy actions are subject to transmission lags as it takes about one year to experience their full effects on inflation. As a result, monetary policy needs to be forward-looking, i.e., based on a forecast.

- A QPM model is a useful tool for forecasting. It encompasses key transmission channels, descriptions of business cycle interactions, and the monetary policy rule. By transmission channels we mean how changes of the policy interest rate transmit to inflation.
- The QPM encompasses the interest rate, the exchange rate, and the expectations channels. The rule ensures that inflation is brought to the target over the forecast horizon and thus it anchors inflation expectations.

Making a forecast with the model means solving the system of model equations over the future horizon. Although our forecast will be model-based, forecasting should not devolve into a technical exercise. To make a solid forecast, our expert knowledge and judgments need to be applied. Macroeconomic narratives behind the forecast play an important role.

A clear and internally consistent narrative helps explain the forecast dynamics and the corresponding monetary policy response to the policy makers and later to the general public.

- As Michael Mussa, a former Chief Economist at the IMF, said: "Monetary policy is not a technical exercise ... Monetary policy is an exercise in political economy where the central bank must be able to explain and justify its actions to politically responsible officials and to the general public."

Baseline Forecast and its Conditionality

The "most probable" future development of the macroeconomic variables featuring in the model is labeled a baseline scenario.

Any forecast is subject to risk and uncertainty related to the model structure and calibration, policy transmission mechanism, and future shocks.

In the context of model-based forecast, we distinguish between forecast risk and forecast uncertainty. While risk exhibits measurable sources and implications, uncertainty is general without clear economic qualifications.

Alternative scenarios, sensitivity analyses, and policy scenarios are used to describe risks. Uncertainty is commonly captured using fan-charts. Both fan-charts and scenarios will be discussed later in this module.

Compiling a baseline scenario includes the steps listed below:

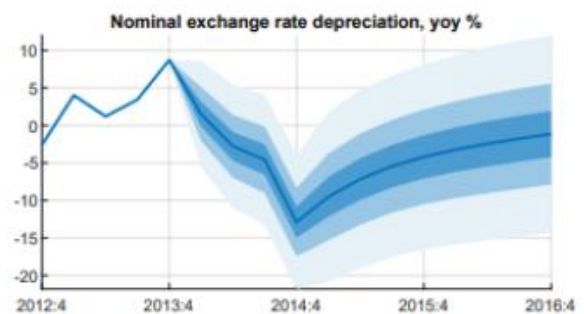
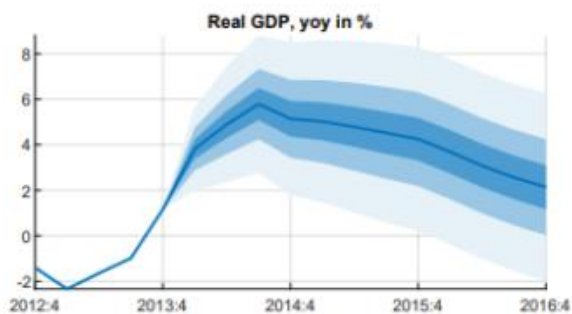
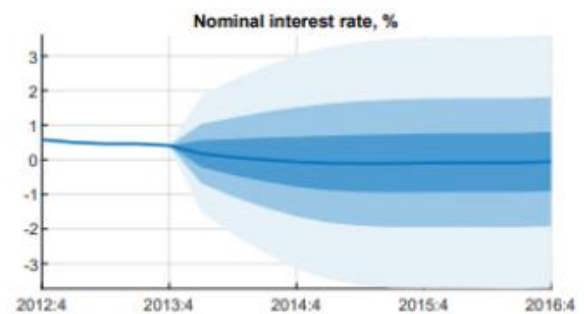
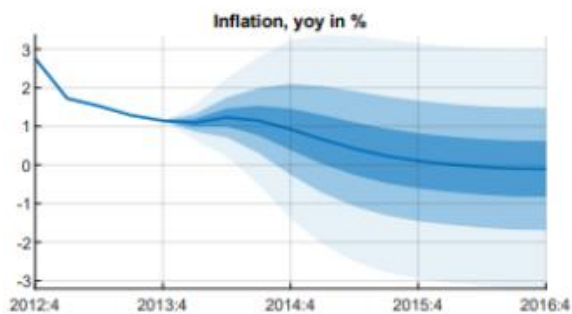


[VIDEO M7_2_STRUCTURE OF A05_FORECAST.M](#)

[VIDEO M7_3_PURE MODEL-BASED FORECAST](#)

Confidence Bands - Fan Charts

Any forecast is uncertain. Fan-charts, as shown below, are commonly used to highlight forecast uncertainty, providing its quantitative description. You can find these fan-charts for key macroeconomic variables in your 'result/Forecast.pdf' on page 1.



In fact, fan charts are confidence bands for potential deviations of future developments of the model variables from their baseline forecast.

- In order to understand the meaning of fan-charts, it can be inspected how they are constructed. A simple autoregressive process (AR) can be used for demonstration. Actual confidence bands for the variables in the QPM can be derived in the similar way, given that the reduced form of the QPM, i.e., solution of the QPM, consists of AR processes, see Module 1 for finding the reduced form.
- An AR process can be written as:

$$y_t = \alpha y_{t-1} + \epsilon_t$$

- Where y_t is endogenous stochastic variable, α is the autoregressive parameter, and ϵ_t is stochastic term. The stochastic term is assumed

$$\epsilon \sim N(0, \sigma^2).$$

- Now variance of forecast y_{t+1} can be computed assuming $y_t \sim N(0,0)$. The zero mean is ad-hoc and changing its value does not alter the variance computed below. The zero standard deviation mirrors the assumption that is observed without uncertainty as all historical data in the forecast compilation. The variance of the one-step ahead forecast is:

$$\text{var}(y_{t+1}) = \sigma^2$$

- Similarly, variances of k-step ahead forecasts are:

$$\text{var}(y_{t+2}) = \alpha^2 \text{var}(y_{t+1}) + \sigma^2 = \alpha^2 \sigma^2 + \sigma^2$$

...

$$\text{var}(y_{t+k}) = \sum_{i=1}^k (\alpha^2)^i \sigma^2 + \sigma^2$$

Having the variance of the forecasts of y computed, fan charts are taken as quantiles of the forecast distribution. Given a linear form of our one-equation model and a normal distribution of the shock ϵ , y_{t+k} is also normally distributed.

Several observations emerge from the computation of variances above:

- **First**, the width of fan-charts depends on the variance of the stochastic term and on parameter.
- **Second**, fan-charts are widening with the length of the forecast horizon. In fact, the variance of the

forecast of y is rising, reaching $\frac{\sigma^2}{1-\alpha^2}$ in the limit.

- **Finally**, fan-charts constructed in the way described above are capturing only uncertainty about future shocks. Uncertainty about the structure of the model and its parametrization is not considered in the computation above. In fact, the model structure and the parameter are taken as given without uncertainty. Adding model structure and parameter uncertainty would further widen the confidence bands.

Expert Judgments - "Hard Tuning"

Adding foreign assumptions to forecasts – ‘hard tuning’

For the foreign sector in the case of our QPM, one would need to impose assumptions about the output gap, inflation, and the policy interest rate in the eurozone. Optionally, assumptions about the equilibrium real interest rate in the eurozone can be introduced.

Imposing any exogenous assumptions and expert judgments on a model forecast is called ‘tuning’ in the modelling jargon. We outline the steps to impose a “tune” in the video below.

[VIDEO M7_4_HARD-TUNING OF VARIABLES IN A FORECAST](#)

Other foreign variables can be tuned on the forecast in the same way. In fact, any variables in the model could be tuned on the forecast in the same way. Bear in mind that the number of ‘exogenized’ data points should equal to the number of ‘endogenized’ shocks periods.

We label the above approach of incorporating exogenous assumptions as ‘hard tuning’.

- ‘Hard’ is used to indicate that the exogenous assumptions on the model variables are hard-wired into the forecast — i.e., irrespective of the subsequent changes in the model calibration or the introduction of other tunes, the variables that were hard-tuned would retain their values.
- In the above case (in the video) of ‘hard-tuning’ the foreign interest rate, the imposed values for RS_RW in 2014Q1-Q4 would be preserved even if one changes the model calibration or the values for foreign natural rate and foreign inflation. Iris would then just recalculate the size of the foreign policy shock (SHK_RS_RW) that is needed to make the corresponding equation hold in all periods.

Expert Judgments - "Soft Tuning"

Adding expert judgments to the forecast – ‘soft tuning’

In this unit you will learn how to apply expert judgments to a model-based forecast. By ‘expert judgment’ we mean any information that we deem important to be reflected in the forecast, but which is not automatically captured by the model dynamics. It needs to be imposed in the form of tuning on top of the model-based forecast. Having this option is important as there might be events or shocks that are different from the common business cycle dynamics captured by the model equations, and we want to be able to reflect these events and shocks in our model-based forecast.

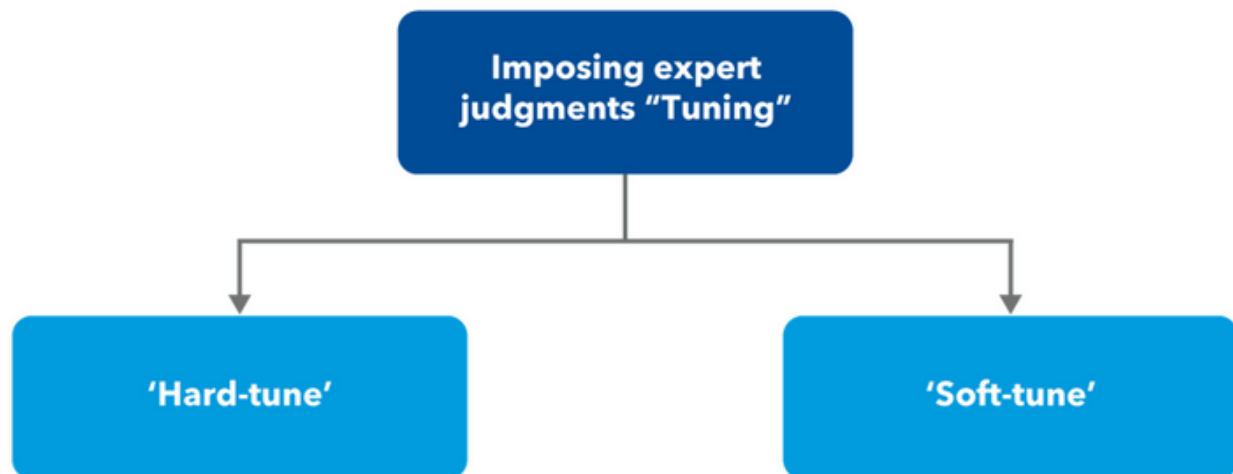
Typically, expert judgments relate to the developments of the domestic variables. Reflecting in the forecast an expected or announced change of VAT taxes affecting prices would be an example of an expert judgment. Suppose that a VAT increase by 10 p.p. starting from January 2015 is announced. Let’s assume that based

on your estimates the VAT increase will raise prices by 7.5% in January. How is such information imposed on our forecast?

Using 'hard tuning' is not a good choice in this case.

- First, we do not know what inflation would be next year. We know the size of the shock— i.e. the added increase in price levels — but not inflation.
- Second, monetary policy might want to react to the anticipated inflation increase (at least to the raising inflation expectations if not to the primary effects of the VAT increase itself). However, using 'hard tuning' would then leave inflation fixed in the tuned quarters, while adjusting the size of the shock. As a result, inflation would stay unchanged despite the reaction of monetary policy. So 'hard tuning' is not an appropriate option.

There are two ways how to impose expert judgments to a model-based forecast: 'hard tuning' and 'soft tuning', shown below.



We should apply the so-called 'soft tuning'. In 'soft tuning' we fix the size of the underlying shock, allowing the variable to adjust. Iris assumes all shocks to be zero over the forecast horizon unless adjusted manually in the input database.

- In the example of our VAT increase, we would need to 'soft tune' the corresponding headline inflation shock: $h.mean.SHK_DLA_CPI(qq(2015,1)) = 4*7.5$;
- When tuning the size of the shock we need to bear in mind that the prefix DLA stands for annualized q-o-q inflation. The annualization requires to multiply the size of the price increase by 4.

Economic Narrative Behind the Baseline Forecast

Instructions: Run 'a05_forecast.m' to compile a baseline forecast. Make sure that the foreign assumptions as declared in lines 49—62 are used. Do not add any extra expert judgment and also do not change the foreign assumptions.

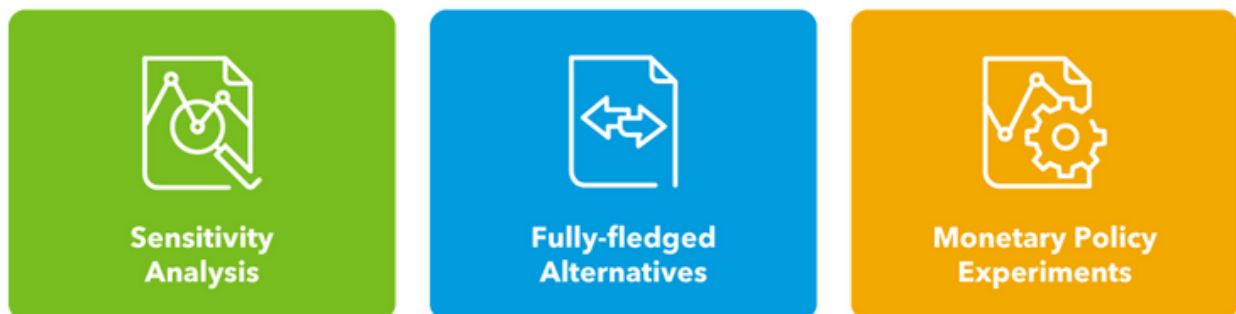
Open 'Forecast.pdf' and inspect the forecast.

[VIDEO M7_5_DECOMPOSITION OF FORECAST TO SHOCKS](#)

Role of alternative scenarios

Alternative scenarios describe key risks to the baseline. While the baseline forecast captures the most probable development of the model variables, alternative scenarios cover the “second most prominent” set of expected future developments and assumptions. The role of alternatives is to show the implications of changing some key assumptions in the baseline and to indicate in which direction the risks to the baseline are skewed.

There are several types of alternative scenarios. Distinguishing these types helps in understanding how they are compiled and how they should be interpreted. The alternative scenario types include the following:



Sensitivity analysis – ‘what if’ scenarios

Sensitivity analysis is a simple model simulation exercise, in which we change only one assumption of the baseline in order to see its implications. These ‘what if’ scenarios are commonly used to show the pass-through of a shock or to demonstrate how the transmission mechanism works. ‘What if’ scenarios are treated as one-off shocks, where only one type of a shock is added.

- *Example:* Nominal exchange rate depreciation captured as an UIP shock; a cost push shock describing tax changes, etc.
- *How to do:* Add a shock to the baseline or change a parameter in the model.

Fully-fledged alternatives

These scenarios are complex testing implications of some economic events assumed in the baseline. There should be a clear economic motivation and a ‘story’ behind these types of scenarios. Usually, a combination of shocks is applied, given the complex nature of these scenarios. Central banks tend to compile one or two ‘fully-fledged’ scenarios per forecasting round at the maximum, as it is relatively costly to do so.

- *Example:* Alternative foreign developments; fiscal consolidation; wider COVID implications, etc.
- *How to do:* Add a set of shocks to the baseline; take simulation results from a satellite model; or impose alternative foreign assumptions.

Monetary policy experiments

Monetary policy experiments evaluate implications of a monetary policy response different from the baseline evaluation. Monetary policy experiments can be compiled assuming only short lived and temporal deviations from the policy rule in the model. Independent monetary policy plays a stabilization role in the economy. It cannot stay inactive in the model as well as in the real world. Inactivity would lead to de-anchoring of inflation expectations and preventing the price stability objective to be fulfilled.

- *Example:* A more aggressive interest rate response; interest rate procrastination, etc.
- *How to do:* Alter monetary policy response by adding monetary policy shocks or changing parameters in the policy rule, etc.

In order to identify an alternative scenario, the following questions are useful to consider:

Are all key assumptions of the baseline scenario robust? What are the domestic, regional and global economic risks?

- *Examples of potential risks:* unanchored inflation expectations; low wage growth with implications to demand; external demand slowdown due to Brexit, etc.

What are the tensions in policy discussion?

- Find points of legitimate disagreement in policy discussion or disagreement with the data and use them to motivate alternative scenarios.
- *Examples* might include risks of prolonged recession along with cost push pressures due to a breakdown of supply chain links, risks of lockdowns with adverse effects on services, or effects of more aggressive policy response.

[VIDEO M7_6_COMPILING AN ALTERNATIVE – STEP 1](#)

[VIDEO M7_7_COMPILING AN ALTERNATIVE – STEP 2](#)

1st scenario – More aggressive monetary policy reaction

Overview/Motivation: Monetary policy experiments are an integral part of monetary policy decision making as these experiments describe implications of monetary policy actions different from baseline.

Inflation is not returning back to the target in our baseline scenario. Moreover, the interest rate trajectory consistent with our baseline forecast reaches negative values, suggesting a need to introduce unconventional monetary policy measures. A commitment to a more aggressive policy response to the expected inflation deviation from the target might help avoid unconventional policy measures in the future.

Let's compile a set of common monetary policy experiments.

[VIDEO M7_8_MONETARY POLICY EXPERIMENTS](#)

2nd scenario – Initial cut of the interest rate

Overview/Motivation: Inflation is not returning back to the target in our baseline scenario. While in the previous task we discussed the case of a permanent shift in monetary policy strategy, what if the preference of a policy maker is to make just the first cut more aggressive.

[VIDEO M7_9_INITIAL CUT OF THE INTEREST RATE](#)

3rd scenario – Procrastination

Overview/Motivation: In this scenario let's assume that the policymaker fails to react and keeps the interest rate unchanged. This is an opposite case to previous experiments.

[VIDEO M7_10_SIMULATION WITH PROCRASTINATION](#)

News Versus Surprise Shocks

Expectations matter in decision making of economic agents and they also play an important role in the QPM. QPM's expectations are rational expectations and are commonly labeled as 'model consistent' expectations.

When assuming a particular shock over the forecast horizon, it matters if the shock is known in advance by the economic agents or if it is a surprise shock. The concept of rational expectations assumed originally that the only sources of uncertainty faced by the economic agents are 'surprise' (unanticipated) shocks. Consequently, structural models as our QPM have been commonly tested using impulse responses to unanticipated shocks only. However, economic agents might learn about shocks in advance, receiving the so-called 'news'. Economic agents make rational expectations but they receive news about future structural shocks and anticipate them and act on them in advance (see Schmitt-Grohé and Uribe, 2008).

We treat our shocks over the forecast horizon as anticipated 'news' shocks. There are two arguments in favor of news shocks in our forecasts.

1+

First, central banks have to collect all available information including anticipated shocks, imposing these shocks on a forecast this is publicly communicated.

2+

Second, any inflation forecast that assumes an active monetary policy should reach the target within the forecast horizon.

VIDEO M7_11_PARTING ADVICE